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A Comprehensive Review of Energy Optimization Techniques in the Internet of Things

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Abstract

The advancement of energy efficiency in the Internet of Things (IoT) and wireless sensor networks (WSNs) is an important research effort, given their rapid application expansion across smart cities and homes, healthcare, agriculture, and industrial automation. This paper conducted a comprehensive survey of existing innovative solutions to challenges focusing on hardware-based, software-driven, and network optimization approaches, alongside artificial intelligence-driven and demand-side energy management, and security-enhanced frameworks. 82 peer-reviewed journal articles and conference papers published between 2021 and 2025 were reviewed, using sources such as IEEE Xplore, ScienceDirect, Web of Science, SpringerLink, and Google Scholar. It identifies significant developments in energy-efficient techniques, including ultra-low-power hardware, adaptive scheduling, bio-inspired clustering, and energy harvesting. Others include intelligent optimization methods(e.g. machine, quantum-inspired heuristics), and blockchain-enhanced security. A structured evaluation process is implemented, following PRISMA guidelines, categorizing studies, and synthesizing findings to highlight technological progress, challenges, and future research directions. The findings show a growing trend towards integrated, multi-objective routing and cross-layer energy optimizations, with significant progress in minimizing energy use, network lifetime and improving security mechanisms. However, challenges like scalability, computational overhead and real-world deployment issues persist. Our study offers valuable insights for sustainable energy management in IoT and WSNs and helps guide future development toward more resilient, adaptable and sustainable energy-aware systems.

Keywords: IoT, WSNs, Energy efficiency techniques, AI-based optimization, Edge computing.

1. INTRODUCTION

The Internet of Things (IoT), a larger application platform built upon wireless sensor networks (WSNs), has revolutionized industries and reshaped how we interact with technology and the environment. IoT connects a massive network of devices equipped with sensors, actuators, and communication modules that collect, analyse, and share data over the Internet [1-5]. These interconnected systems allow devices to operate independently, enabling smarter decision-making and driving

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transformative innovations across sectors such as smart homes, healthcare, smart cities, industrial automation, agriculture, and transportation [1-6]. In recent years, the development of miniaturized sensors and actuators, along with widespread access to high-speed internet, has supported the rapid spread of smart devices across domains [2,3]. This is evident in remote sensing and data capture, where fog and cloud services play a vital role. Current projections estimate that by 2030, over 75 billion IoT devices will be in use, underscoring their critical role in shaping modern infrastructure [1,5, 6]. IoT systems are more scalable than traditional WSNs, using internet-enabled devices, along with fog and cloud platforms, as gateways to the wider network.

While the increase in the number of IoT devices is beneficial in terms of efficiency and innovations, it also poses energy efficiency (EE) challenges, as many IoT devices rely on limited power sources, especially in remote or mobile settings [1-15]. The battery-powered sensors tagged to these devices, such as smartphones, smart electric appliances, smart office equipment, cars, and so on, often consume large amounts of energy. Excessive energy consumption reduces device lifespan, increases operational costs, and contributes to environmental degradation [1-15]. This challenge is further exacerbated by the remote locations of these nodes in some cases, at which the maintenance is highly impractical, resulting in constraints in sustaining the operation for long periods [1-15]. Tackling this issue requires innovative solutions that optimize energy use, integrate renewable energy sources, and balance performance with resource management.

Several optimization techniques and energy management systems are employed across different layers of the network architecture to optimise energy use. This includes lightweight encryption, energy-efficient routing protocol, duty cycle, edge computing, data compression, power-aware scheduling, energy harvesting (EH), battery management systems, and network traffic optimization[1-15], etc., have been introduced to help manage power consumption in IoT devices and networks to prolong the device's lifespan. While these solutions exist in the IoT ecosystems, energy use remains a critical challenge. Research has shown that energy consumption is the major barrier to scaling IoT systems as it constrains the processing of IoT network functionalities. Studies have shown that communication and sensing activities consume a significant portion of power[1-8]. Thus, optimizing EE is essential to ensuring the reliability, scalability, and ecological sustainability of IoT ecosystems.

Given the above background, this paper conducts a review to systematically evaluate current strategies, technologies, and challenges in energy management for IoT systems. It is intended to explore and integrate recent developments in energy-efficient design and operation, focusing on hardware innovations, software algorithms, network protocols, artificial intelligence (AI)-driven optimizations and

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demand-side management while highlighting important trends, techniques, and future directions. This study offers valuable insights into developing a new energy-aware framework that helps IoT devices extend their lifespan by using resources more efficiently, meeting the growing need for resource-efficient technologies. The main contributions of this paper are:

1) Provided a structured review of recent advances in energy-efficient techniques for IoT and WSNs, following the Systematic Reviews and Meta-Analyses (PRISMA) guidelines and drawing from a range of peer-reviewed sources.
2) Identified and categorized energy management strategies, covering hardware-level designs, software-based methods, network and AI-driven optimizations, etc., with attention to trends like federated learning (FL), bio-inspired, quantum-based, multi-objective, blockchain-supported security and reliability, and so on.
3) Outlines several important research directions, focusing on scalable, deployment-aware solutions that combine machine learning (ML), edge computing (EC) and decentralized architectures to support sustainable, efficient IoT systems

The remaining parts of the paper are organized as follows: Section 2 presents the background information and related works, and Section 3 presents the methodology. Section 4 presents the analysis of existing IoT energy-efficient strategies, Section 5 presents the findings discussions and possible research direction while Section 6 concludes the paper.

2. LITERATURE REVIEW

2.1. IoT Energy Efficiency

The architecture of IoT systems is organized into multiple layers with each performing specific functions that are critical to the system's operation. The sensing layer is responsible for collecting environmental or operational data via sensors and actuators. The network layer allows communication through protocols like ZigBee, LoRaWAN, or cellular networks, while the application layer processes data for analytics, visualization, or decision-making [1][9]. Given the distinct layers, the energy utilization across them differs significantly. Particularly, the network layer often accounting up to 70% of the total energy used by IoT devices, which makes it the most power-intensive component [3, 5, 8]. To deal with EE challenges, several strategies have been designed, developed, and deployed such as hardware-based, software-based, and network-based such as optimizing communication protocols and minimizing redundant data transmission. In addition, EC at the application layer has been introduced to reduce energy use by processing data next to the source. As shown in Figure 1, collectively, the goal is to ensure devices' efficiency and increase the network lifespan.

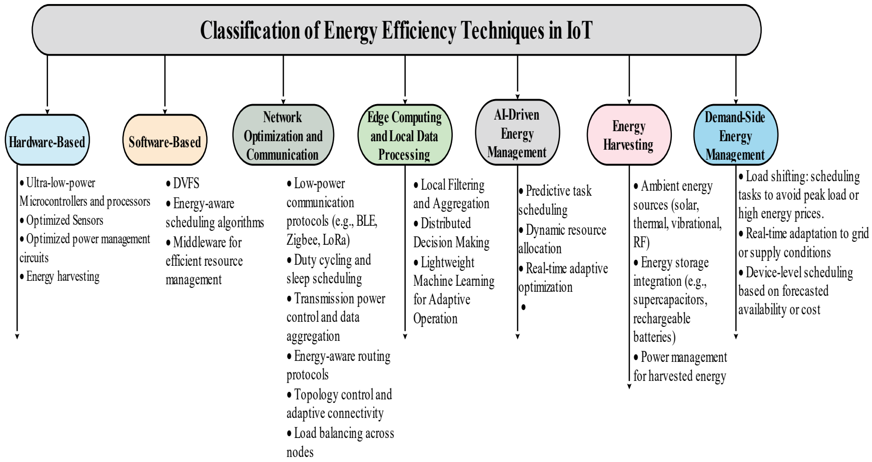

Figure 2. IoT energy efficiency techniques

Furthermore, EE in the IoT ecosystem relies on hardware and software techniques to minimize power consumption while maintaining system reliability. Hardware-based methods include ultra-low-power microcontrollers, event-driven sensors, and optimized circuits that dynamically adjust voltage and clock speed to reduce energy use [3, 9]. These are complemented by EH mechanisms, such as solar or piezoelectric elements, enabling extended operation without frequent battery replacements [9-11]. Outdoor solar panels and RF or thermal harvesting increase autonomy in urban and industrial settings, achieving up to 80% energy self-sufficiency. Equally, software techniques work alongside hardware optimizations, dynamically adjusting system behaviours based on workload. Dynamic voltage and frequency scaling (DVFS) reduce processing demands, cutting energy use by over 90% in low-traffic conditions. Task scheduling and middleware enhance resource distribution by regulating sensor activity to minimize unnecessary operations [3, 9, 14]. Additionally, data compression lowers communication energy costs by 30–50%, depending on data type, further improving overall efficiency.

Beyond individual devices, EE is shaped by communication and network-level strategies. Wireless communication is energy-intensive, leading to the use of duty cycling, adaptive transmission control, and data aggregation to reduce transmission frequency and duration. Low-power hardware designs and duty cycling alternate between active and sleep modes to conserve energy [1, 3, 5, 8, 9]. At the network level, energy-aware routing, topology management, and load distribution extend the system lifespan by balancing energy demand [1, 4, 14]. In addition, EC supports local processing, minimizing cloud storage reliance and cutting transmission-

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related energy use by up to 60% in dense networks [9]. ML and AI, such as deep learning (DL), FL, and reinforcement learning (RL), enable real-time adaptation to usage patterns and environmental conditions. These learning-based models optimize scheduling and resource allocation across networks [2, 9]. EH and renewable energy integration (REI) [9-11, 13] further align device operations with available energy sources or grid conditions [7, 14]. EH, combined with EC allows devices to process data locally using renewable power to reduce transmission dependence [13]. Likewise, demand-side energy management (DSEM) complements this by optimizing electricity consumption and lowering costs. Studies show that integrating solar harvesting, adaptive sampling, and similar approaches can cut energy use by up to 60-80%, improving the efficiency and sustainability of IoT systems. These energy-aware techniques improve network lifetime and reliability while mitigating environmental impact. However, achieving optimal balance requires managing trade-offs [1]. For example, improving data accuracy may require more frequent transmissions, which in turn increases energy use. Likewise, improving security or fault tolerance can introduce overheads that impact latency or EE. Consequently, researchers are now focusing on multi-objective optimisation to balance the competing demands.

(a) (b) (c)

Figure 2. (a) DVFS architecture, (b) Zigbee module, (c) Solar panel

2.2. Related Works

This section presents selected reviews and surveys on EE optimization in the context of IoT and WSNs. These works cover data aggregation, fault tolerance, routing protocols, low-power design, EH, and communication strategies. Several studies have reviewed efficient data aggregation and routing. Begum and Nandury [1], Bharany et al. [2], and Khan et al. [4] reviewed methods to reduce energy use while maintaining reliable communication. Begum and Nandury [1] provided a general overview of data aggregation strategies, while Khan et al. [4] focused on fault-tolerant mechanisms in green cloud computing. Bharany et al. [2] concentrated on energy-efficient routing in underwater sensor networks (UWSNs), incorporating ML techniques to extend network lifetime and reduce energy usage. Low-power design has also been a prominent topic. Kumar et al. [3], Barge and Gerardine [8], and Almudayni et al. [14] surveyed various techniques such as clock

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gating, voltage and frequency scaling, and AI-based methods to improve energy use in IoT systems. Kumar et al. [3] also highlighted the trade-offs involved in achieving a balance between security, interoperability, and performance. Almudayni et al. [14] proposed bio-inspired algorithms and fuzzy logic-based approaches, while Barge and Gerardine [8] offered a detailed architectural analysis aimed at extending battery life.

Furthermore, EH has been the focus of studies by [11], [5], [10], and [13], each proposing a way to support self-sustaining IoT systems. Study [11] adopted a layered view, mapping EH sources to specific device functions. Study [5] examined LoRa-based methods for conserving energy, while [10] supported its analysis with real-world case studies. Study [13] developed a structured classification of EH techniques, optimization strategies, and efficiency metrics. Similarly, communication methods also play a central role in energy optimization. Souri et al. [12], [7], and Ali et al. [15] investigated communication protocols, scalability, and intelligent approaches to reduce energy overhead. Souri et al. [12] surveyed IoT communication trends, with attention to security and scalability. Lastly, authors in [7] linked smart building energy management to IoT policy constraints, and Ali et al. [15] examined energy-efficient communication strategies in underwater IoT (IoUT) environments.

Table 1. Summary of related works

Study	Focus	Findings	Key Strengths	Limitations
[1]	Energy-saving techniques for IoT devices using LoRa	Identifies energy parameters (transmission power, bandwidth); categorizes techniques (harvesting, transfer, conservation); analyzes geographic research trends	Rigorous SLR; broad coverage (44 studies); dual-layer focus (IoT and LoRa)	Limited empirical validation; lacks comparative metrics; scalability not analysed
[2]	Fault tolerance in green cloud computing	Classifies fault-tolerance approaches (proactive vs. reactive); examines energy-fault	Systematic classification; identifies gaps; and addresses automation and user control	Mostly theoretical; lacks real-world validation.

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Study	Focus	Findings	Key Strengths	Limitations
		trade-offs with AI/ML.		
[3]	Low-power design for IoT devices	Reviews hardware (DVFS, MEMS sensors), software, and EH methods	Broad scope; real-world applications; includes case studies	Limited quantitative analysis: security-power trade-offs not addressed
[4]	Energy-efficient routing in UWSNs	Uses ML for adaptive routing; addresses cross-layer and security considerations	Strong taxonomy: acoustic channel constraints considered	No performance comparisons; lacks experimental validation
[5]	Energy-saving schemes in IoT-LoRa	Categorizes energy parameters and conservation methods; notes geographic research trends.	Structured SLR; regional trends identified	Mostly descriptive; data limited to pre-2022
[6]	EE in SDWSNs	Reviews major energy consumers; discusses routing, sleep scheduling, and AI-based optimization	Comprehensive challenge overview: future directions outlined	No deployment studies; lacks empirical testing
[7]	IoT applications for energy management in smart buildings	Review architecture, protocols, adoption barriers, and application domains	Multidimensional perspective; includes policy insights	Mostly descriptive; no case studies or evaluations
[8]	Architectural low-power design for IoT	Covers power gating, voltage scaling, hardware acceleration	Technical depth; links architecture to IoT constraints	No experimental results; lack combined method evaluations
[9]	EE in IoT systems	Integrates hardware, protocols, AI, and renewables;	Wide scope; links AI to energy goals	No quantitative comparisons: implementation

Study	Focus	Findings	Key Strengths	Limitations
		promotes cross-layer optimization		issues not discussed
[10]	EH techniques for IoT	Identifies EH sources and real-world strategies	Conceptual clarity; includes practical case studies	No comparative analysis of EH efficiency
[11]	EH within IoT layered architecture	Maps EH sources to IoT layers; discusses storage and power management	Framework aligns EH with system needs	Limited technical depth on implementation
[12]	IoT communication strategies	Review five strategy types, technologies, and evaluation metrics	Clear taxonomy; identifies open challenges	Lacks critical analysis; English-only literature
[13]	Energy management in IoT	Covers energy efficiency, harvesting, and optimization techniques	Thematically organized; domain-spanning	No performance evaluation; lacks technical detail
[14]	Causes of energy inefficiency in IoT	Proposes a multi-layered framework using optimized protocols, fuzzy logic, and bio-inspired methods	Strong conceptual depth; integrates AI with communication efficiency	No empirical validation; lacks comparative performance analysis
[15]	Energy-saving techniques for IoT devices using LoRa	Identifies energy parameters (transmission power, bandwidth); categorizes techniques (EH, transfer, conservation); analyzes geographic research trends	Rigorous SLR; broad coverage (44 studies); dual-layer focus (IoT and LoRa)	Limited empirical validation; lacks comparative metrics; scalability not analysed

As shown in Table 1, recent IoT EE reviews reflect a broad but disjointed focus, with most studies targeting isolated techniques instead of pursuing integrated solutions. Studies like [5], [10], and [11] focused on EH, while [4] and [12] explored network optimization and routing strategies but lacked discussion on hardware-based EE and cross-layer approaches. Additionally, [5], [10], and [11] provided limited quantitative comparisons, resulting in a lack of assessing the deployment trade-offs. Research on low-power design and underwater IoT EE in [3], [8], and [15] overlooked security overhead implications, while Ali et al. [15] examined REI and software-driven efficiency. Studies [6], [13], and [14] addressed optimization across IoT layers but did not analyse interactions between layers in multi-protocol environments. Likewise, Poyyamozhi et al. [7] and Manohar & Dharini [9] discussed smart energy management but failed to include standardization challenges in protocol compatibility, interoperability, and regulatory frameworks. Given the above studies, it is important future research should adopt a more integrated approach, incorporating advancements in hardware, software, communication, EH, and AI-driven optimization. The purpose of this paper is to explore these gaps with collaborative, cross-layer strategies to provide scalable, adaptable solutions tailored to evolving IoT applications, the purpose of this paper.

3. METHODS

This employs a systematic literature review approach to analyze advancements in IoT EE techniques for resource-constrained devices and large-scale deployments. It focuses on hardware-based, software-based, and network efficiency, AI-driven energy optimizations, DSEM and security-enhanced frameworks. Relevant peer-reviewed journal articles and conference papers from 2021–2025 were selected for this review. Sources include IEEE Xplore, ScienceDirect, Web of Science, SpringerLink, and Google Scholar. The selection criteria focused on relevance to the topic, citation impact, evidence of technological innovation, and empirical validation to ensure high quality in the study. Our data extraction followed a three-stage process: (1) Initial screening, filtering abstracts and keywords to align with inclusion criteria; (2) Categorization, classifying studies into individual and hybrid techniques; and (3) Trends and gap analysis, synthesizing findings to highlight key developments, limitations, and future research directions. The evaluation process combined qualitative and quantitative analysis, following the Preferred Reporting Items for PRISMA guidelines [16] to ensure transparency, reproducibility, and structured reporting.

Using PRISMA, search terms included “energy efficiency techniques in IoT,” “IoT energy management techniques,” “hardware-based EE techniques,” “software-based EE techniques,” and “AI-based EE optimization,” guided by Boolean operators “OR” and “AND.” Initially, 210 relevant articles were retrieved, with 8 duplicates removed, leaving 155 studies for screening. Following the eligibility

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assessment, 55 studies were excluded due to a lack of empirical analysis or duplicate contributions, resulting in 82 selected papers. Inclusion criteria focused on relevance to IoT energy management, technological innovation, empirical validation, theoretical models, and practical implementations, including future research discussions. Exclusion criteria filtered out studies outside IoT/WSN scope, outdated papers, duplicates, and inaccessible full texts.

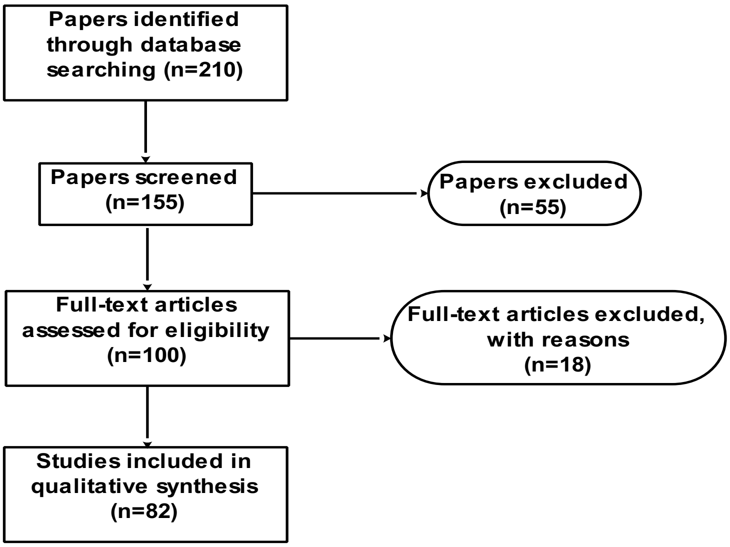

Figure 3. PRISMA process of selected studies

4. RESULTS AND DISCUSSION

4.1. Energy Efficiency State-of-The-Art

This section analyses various EE techniques used in IoT systems to improve device performance and network lifetime. In practice, EE is rarely achieved through a single method. Most real-world solutions combine, hardware, software, networking, and communication and intelligent-based approaches to meet energy demands in different conditions. In the studies reviewed, around 95% of the techniques were hybrid-based, for instance, combining low-power hardware, REI, AI-driven optimization, and dynamic energy management. These strategies not only improve reliability and lifespan but also help reduce environmental impact. These studies are summarized in Tables 2 to 13. This shows that careful design remains crucial to balancing cost, complexity, and dependability in energy-efficient IoT deployments.

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1) Software-based Methods

Software-based techniques or smart algorithms improve EE in IoT devices by managing tasks intelligently, even on low-power hardware. These approaches significantly reduce energy use via smarter software execution and some of the studies are summarized in Table 2. Liu et al. [17] developed a task-scheduling algorithm for EC systems using heterogeneous multicore processors (HMPs) to minimize energy use while ensuring deadline adherence. Their approach integrates task prioritization, core-aware mapping, and predictive DVFS. Tasks are ranked based on deadlines and dependencies, mapped using a performance-execution-time-power suitability score, and assigned DVFS settings based on estimated energy consumption. Experiments on an ODROID-XU4 platform demonstrate significant energy savings and consistent deadline adherence, making it a scalable solution for edge scheduling. Likewise, Ketshabetswe et al. [18] improved two adaptive lossless data compression algorithms: ALDC and FELACS, to reduce the energy cost of data transmission in WSNs. They enhanced ALDC by dynamically selecting shorter Huffman codes, boosting energy savings from 73% to 77%. FELACS was refined with an outlier detection method that reduces data variability, improving both compression and accuracy. Performance evaluations using real-world datasets identified an optimal block size of 1000 samples for efficient transmission.

Beyond software techniques, EC enhances EE by enabling local data processing. Bhatia [19] proposed a hierarchical IoT-edge framework that integrates inactivity modes, load balancing, and predictive algorithms to optimize power consumption. The system manages sensor activity, predicts idle periods, and reallocates resources while dynamically switching IoT nodes based on battery levels and usage patterns. A medical campus deployment validated its effectiveness, showing a 29.46% reduction in energy use and improved network stability with a lower packet loss ratio of 0.51%. Hua et al. [20] also introduced a mobility-aware task scheduling framework for edge-cloud computing, enabling flexible task execution between local devices, edge servers, and the cloud. They formulated the problem as a mixed-integer program (MIP) and proposed a heuristic algorithm (MAH) to overcome computational complexity. Simulations demonstrate a 93% reduction in mobile device energy use while maintaining low-latency performance, particularly as time slots increase. Moreover, Harb et al. [21] designed CLARA, an adaptive sampling and fault-tolerant recovery method for periodic WSNs, leveraging spatial-temporal correlation and smoothing algorithms. While effective under stable conditions, CLARA's reliance on fixed parameters may limit performance in dynamic or heterogeneous settings. Small-scale real-world evaluations confirm its practicality.

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Table 2. Summary of software-based EE methods

Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
[17]	EE scheduling for edge devices	DVFS, task-level optimization	Edge nodes (ARM big.LITTLE)	Energy-aware scheduling, predictive task-core mapping	Energy use, deadline miss rate	20.9% power reduction	Migration overhead ignored
[18]	EE via adaptive compression in WSNs	Huffman-optimized ALDC, FELACS outlier detection	WSN nodes (env. data)	ALDC with Huffman; FELACS tuned for accuracy	Energy saved, compression ratio, codeword size	77% energy saved; 50% smaller codeword	High compute cost; untested on diverse sensors
[19]	IoT-edge hierarchical EE framework	Inactivity mode, resource allocation, predictive models	IoT-edge with EE gateways, sensors	3-layer architecture + blockchain security	Energy use, PLR, system stability	29.46% energy saved; PLR 0.51%; MAS 84.69%	Narrow test scope; theory limits generalization
[20]	Mobility-aware edge-cloud EE	Power control, offloading, scheduling	Mobiles, edge/cloud servers, LTE BS	Dynamic cost matrix; iterative MIP	Energy, latency, QoS compliance	MA-MIP saves 93%; MAH efficient & simpler	Single BS model; MIP scales poorly
[21]	Boost WSN EE via adaptive sampling	Data reduction, fault tolerance	Cluster-heads, sink	Sampling rate + fault-tolerance algorithms	Alive nodes, energy, packets, lifespan	64% data drop; error <0.15 (MA)	Needs post-deployment tuning

2) Software-based with AI-optimization Methods

As stated above, hybrid dynamic approaches such as software-based EE and AI-based optimization are integrated to improve IoT energy management. They utilize real-time data from sensors and smart meters, which are analysed by AI-driven algorithms to predict energy demand and allocate EE. Unlike traditional methods, these AI-drive technologies continuously adapt to changing conditions, ensuring optimal resource allocation, and minimizing energy waste. Several studies have contributed to AI-based energy optimization integrated with security and fault tolerance to improve sustainability and reduce energy use as summarized in Table 3 and Table 4. Aljohani [22] proposed a transformer-based DL framework for energy demand forecasting in smart city IoT networks. It captures spatial and temporal dependencies to generate real-time predictions, integrating IoT devices, sensors, and smart grids via cloud computing for dynamic energy management.

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Case studies show reduced energy use, costs, and emissions, with strong stakeholder support. Similarly, Raval et al. [23] combined multi-agent systems and genetic algorithms (GAs) for decentralized energy management. Their energy transparency protocol modelled consumption as sensing, processing, and communication functions. The RL-based fuzzy logic with GAs improves sensing and energy usage across IoT swarms, achieving a 19% reduction in consumption rate and 40% lower total energy use per time step, improving stability. Wang et al. [24] also developed MADC, a scalable DRL algorithm for improving RPL routing in IIoT networks. They used centralized training and decentralized execution alongside lightweight actor networks for real-time decisions, integrating multi-scale convolution and multi-head self-attention for robust evaluation. Simulations show superior energy efficiency, packet delivery, and queue loss compared to existing RPL methods. In the same vein, Mutombo et al. [25] developed EER-RL, an RL-based energy-aware routing protocol for IoT networks. They employed Q-learning in a cluster-based model, nodes select next-hop routes based on residual energy and hop count to enable decentralized learning without global state reliance. Simulations indicate improved energy efficiency and network lifetime over LEACH and PEGASIS, particularly in larger networks.

Furthermore, Godfrey et al. [26] introduced a distributed opportunistic scheduling (DOS) protocol using RL for SDWSN in IoT, optimizing EE. The RL agent dynamically prioritizes objectives like energy use, load balancing, and link quality using real-time confidence estimates and shaped rewards. NS-3 simulations show that DOS-RL surpasses OSPF and SDN-based Q-routing in packet delivery, latency, and EE across various conditions. In a similar study, Rashid et al. [27] suggested an adaptive CNN for energy-efficient human activity recognition (AHAR) on low-power wearable devices. Instead of early-exit decisions based on classification confidence, they introduced an Output Block Predictor (OBP) using statistical features to determine whether to use a lightweight or full CNN path during inference. Validation on two public datasets confirms improved accuracy, reduced energy consumption, and lower memory usage compared to state-of-the-art methods. AHAR runs efficiently on microcontrollers, making it suitable for wearable health monitoring. Balakrishnan and Rajkumar [28] proposed an improved metaheuristic algorithm for optimizing cluster head (CH) selection in IoT-based healthcare systems. Their method is based on the Mayfly optimization algorithm (MOA) with an active elite approach (AEA). It dynamically adjusts the search space to create elite candidates and avoid local optima, ensuring balanced energy use and extended network lifetime. Evaluated within a broader system combining biometric authentication, RL-based routing, and ECC for secure transmission, the method shows effectiveness. EMOA-AEA outperforms existing methods in energy use, network lifetime, and throughput, demonstrating AI-improved clustering as a valuable technique for medical IoT.

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To improve EE and communication security in EVs within the smart grid, Bhaskar et al. [29] proposed an IoT, ML, and blockchain-based system. In this case, IoT sensors enable real-time monitoring of battery levels and location, while a Random Forest classifier optimizes charging station selection. Additionally, a permissioned blockchain with ECC encryption ensures secure authentication and transactions. Simulations show a 94.5% accuracy in station selection, reduced wait times, lower communication overhead, and decreased charging costs. Likewise, Liu et al. [30] introduced QEGWO, a clustering algorithm combining quantum mechanics-inspired clustering with AI-based Gray Wolf Optimization (GWO) to improve EE in Industrial WSNs (IWSNs). The model optimizes residual energy, intra-cluster distance, and base station proximity, combining a simplified quantum operator and dynamic elite pool for better global search and convergence speed. Simulations confirm superior performance in network lifetime, energy distribution, and delay. Ali et al. [31] equally developed E-FLZSEP, an adaptive fuzzy logic-based protocol for CH selection in WSNs. It integrates voltage, node density, and base station distance to improve cluster lifespan and data delivery efficiency. The authors highlight fuzzy logic's ability to handle nonlinearity, combining clustering with multipath routing for improved fault tolerance and load balancing.

Table 3. Summary of AI-driven software-based EE methods

Ref	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
[22]	AI-based energy optimization in smart cities	Dynamic load prediction, real-time adaptation	IoT, smart grids, cloud, urban infra	Edge DL models; real-world validation	Energy use, cost, model accuracy	Better efficiency reduces the cost	Narrow scope of sustainability
[23]	Decentralized AI energy management	Adaptive sensing, AI-based control	IoT swarms, LPWAN (LoRa, Sigfox)	RL adaptation; GA optimization	Energy rate, stabilization	40% energy reduction	Limited interference handling
[24]	Scalable EE routing in IIoT	DRL with centralized training distributed execution	IIoT nodes (RPL)	Actor-network with attention & dual critic	Energy, lifetime, delivery ratio	+40% lifetime, +16.7% delivery	Simulation-only; potential complexity
[25]	RL-based routing in IoT WSNs	Q-learning with residual energy reward	Clustered IoT WSNs with power limits	RL for adaptive routing	Lifetime, energy, scalability	Outperforms LEACH & PEGASIS	Memory cost; not deployed
[26]	Multi-objective EE routing	Shaped-reward RL routing	SDWSN (sensing/cont	CMOMDP, ε-greedy Q-learning	PDR, delay, energy	10–20% better PDR,	Simulation-only;

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Ref	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
	in SDWSN-IoT		rol/app layers)			lower delay	scalability unclear
[27]	EE CNN for HAR on edge	Hardware-aware exec path control	EFM32 MCU, multi-output CNN	Tested with HAR datasets	Energy, memory, runtime, F1	12% energy saved, similar accuracy	HAR-specific; dataset bound
[28]	CH selection in IoT healthcare	Energy-aware clustering, secure routing	Body sensors, sink, crypto modules	Elite-based metaheuristic strategy	Lifetime, throughput, security	43.9% better through put, longer life	Encryption + optimizatio n overhead
[29]	Secure, efficient EV energy managemen t	EE EV charging, secure transactions	EV sensors, ML models, blockchain, chargers	ML for charging; blockchain security	Accuracy, wait time, overhead, capacity	94.5% accuracy ; 15.45% ↓ wait time; 63% ↓ overhea d	Cost and scalability concerns
[30]	EE clustering in IWSNs	EE clustering, multihop transmissio n	Static nodes, CHs, BS	Simulated in diverse IWSN setups	Energy, delay, longevity	Beats baseline s in energy & delay	Simulation-only; fixed-node assumption
[31]	Lifetime extension via CH balancing	Adaptive CH election by node energy	CHs, BS	Fuzzy logic + multipath routing	Node death, alive %, throughput, energy	+30% lifetime, –35% energy	Low adaptability to topology change

Rami et al. [32] introduced EECHIGWO, an improved GWO-based algorithm for energy-efficient CH selection in WSNs. It tackles premature convergence and the imbalance between exploration and exploitation by combining residual energy, sink distance, cluster head balancing, and intra-cluster distance into the fitness function. Simulations show improved network stability, energy use, network lifetime, and throughput compared to existing protocols in optimizing CH selection to balance energy use and extend node lifespan. Similarly, Devassy et al. [33] suggested NBA, a hybrid clustering protocol combining LEACH with the Dragonfly Algorithm (DA) to improve EE in WSNs for IoT applications. In the approach, NBA optimizes CH selection by modelling it as an optimization problem, incorporating dragonfly-inspired behaviours for better energy balance using swarm intelligence. Simulations confirm superior packet delivery, network longevity, and scalability over standard LEACH, emphasizing bio-inspired AI strategies for energy-efficient IoT networks. Moreover, Tewari and Tripathi [34] developed NFEER, a neuro-fuzzy clustering protocol for IoT-enabled WSNs to optimize energy use in battery-powered sensor nodes. In their method, CH selection is based on distance to sink, cluster size, and residual energy, mitigating hotspot issues using a neuro-fuzzy inference system. The protocol surpasses PSO-Kmean, BMHGA, and FSO-PSO in network lifetime, stability, and throughput, though its reliance on a static sink and ideal transmission conditions remains a limitation. In a similar but different approach, Vaiyapuri et al. [35] suggested CBR-ICWSN, a hybrid clustering and routing protocol for efficient data collection in IoT-enabled ICWSNs within Mobile EC (MEC) settings. They employed black widow optimization (BWO) for CH selection and oppositional artificial bee colonies (OABC) for routing to ensure scalability and resource constraints in large networks. Simulations show improved energy efficiency, reduced packet loss, and higher network throughput compared to traditional protocols.

Still, on clustering and routing for EE, Senthil et al. [36] focused on the challenges of IoT-based WSNs by introducing Orphan-LEACH (O-LEACH) and two hybrid optimization algorithms, SA-LSA and PSO-LSA. O-LEACH mitigates orphan node issues by allowing nodes outside standard clusters to act as gateways or form sub-clusters to improve coverage and reduce data loss. PSO-LSA and SA-LSA improve CH selection and routing using global and local search techniques. Experimental results show PSO-LSA's superiority in cluster formation, delay, packet loss, and network lifetime, proving its suitability for energy-constrained IoT scenarios. In parallel, Cherappa et al. [37] proposed a hybrid clustering and routing strategy combining Adaptive Sailfish Optimization (ASFO) with K-medoids clustering and E-CERP, a cross-layer routing protocol. The AI-driven clustering optimizes CH selection based on energy and proximity, while E-CERP enables efficient multi-hop routing. Simulations show enhanced energy savings and packet delivery accuracy, outperforming existing methods and proving the ASFO-K-medoids and E-CERP approach effective for WSNs. In the same way, Lakshmanna et al. [38] developed IMD-EACBR, an energy-aware cluster-based routing scheme integrating an improved Archimedes optimization algorithm (IAOA) for CH selection and teaching–learning-based optimization (TLBO) for multi-hop routing. While clustering considers energy levels, node distances, and network topology, routing prioritizes nodes with higher residual energy and shorter transmission distances. NS-3 simulations show substantial improvements in network lifespan, energy efficiency, and data delivery over other metaheuristic protocols.

Table 4. Summary of AI-driven software-based EE methods

Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
[32]	Improve EE &	Metaheuristic clustering	WSN nodes, BS, fixed multi-hop	MATLAB-based dynamic CH model	Lifetime, throughput, node	+333.51 % stability,	Simulation-only; real-world

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Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
	stability in WSNs				deaths (FND/HND/LND)	extended lifetime	scalability untested
[33]	Lower energy use & extend WSN life	Bio-inspired CH selection	WSN nodes, CHs, BS	Simulated with 100 nodes (MATLAB)	Live nodes, packet ratio, energy use	More live nodes, better delivery	Needs tuning; lacks deployment
[34]	Enhance routing via neuro-fuzzy logic	Neural, fuzzy logic for CHs	Heterogeneous WSN nodes, CHs, Sink	Compared NFEER to PSO-Kmean, BMHGA, FSO-PSO	Stability, lifetime, throughput, energy	+28% stability; 103.5–142.25 % longer life	Fixed sink; ignores physical layer factors
[35]	Better data collection & routing	Swarm, bio-inspired routing	WSN nodes, CHs, Master Station	Custom protocol with BWO/OABC	Lifetime, delay, energy, loss, PDR	Higher efficiency, lower delay	Simulation-only; ML integration unexplored
[36]	EE via orphan node management	Swarm/metaheuristic routing & clustering	WSN nodes, CHs, BS, orphans, sub-clusters	Hybrid CH and path selection protocol	Cluster formation, delay, loss, lifetime	PSO-LSA cuts delay, boosts lifetime	Not tested in real settings; scalability unclear
[37]	EE clustering & routing in WSNs	Cross-layer routing, EE clustering	WSN nodes, CHs, BS, routing stack	Simulated with 500 nodes	Energy, lifetime, PDR, delay, throughput, jitter	E-CERP: 1.97 mJ vs. 7.75 mJ, 100% PDR	Static sensors; no mobility analysis
[38]	EE routing for IoT-assisted WSNs	Cluster-based routing optimization	WSN nodes, CHs, BS, optimizer	Simulated in NS-3.26	Lifetime, node status, energy, throughput, PDR	PDR 95.5%, Longer life, better throughput, lower energy use	Requires tuning; no real-world test

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3) Software-based with Edge Computing, DSEM and AI-optimization

This section analyses EE techniques that combine software-driven methods, EC, and AI-based optimization to improve adaptability. Additionally, while some approaches incorporate security, others employ fault tolerance for system resilience. These algorithms improve power use by activating devices only when needed, while EC minimizes latency and cloud-related costs through local processing. Energy usage is optimized via demand prediction, automated control, and continuous energy flow refinement. Table 5 summarizes key studies. Akbari et al. [39] suggested a decentralized method for optimizing virtual network function (VNF) placement. This is mostly used in UAV-assisted Mobile EC (MEC) systems for smart agriculture, balancing timely data processing based on Age of Information (AoI) and EE. They employed a decentralized partially observed Markov decision process (DEC-POMDP) to model UAV interactions as well as an asynchronous federated deep Q-network (AFDQN) approach for collaborative VNF placement without raw data sharing. Simulations confirm lower AoI and higher EE compared to centralized methods, making it ideal for agricultural IoT. In the same vein, Ruby et al. [40] developed a two-tier FL architecture to deal with inefficiencies in traditional centralized FL systems under non-IID data distributions and energy constraints. The framework features IoT clients, low-altitude UAVs for edge aggregation, and a high-altitude UAV as the central aggregator. By solving an optimization problem through dual decomposition and bisection search, the system minimizes computation and communication energy under time constraints. Offline and online client scheduling prioritizes participants based on model divergence weight and EE. Simulations using real-world data demonstrate reduced energy consumption and improved learning accuracy compared to existing methods.

4) DSEMs with AI-optimization

This section focuses on AI-driven optimization within DSEM, which dynamically adjusts consumption based on real-time grid conditions to improve efficiency and reduce costs. Table 5 summarizes key findings. Khodaparast et al. [41] suggested an energy-efficient DRL-based multi-agent framework for data collection in UAV-assisted IoT networks. The approach is divided into: UAV navigation, sensor power management, and multi-UAV coordination. Each is tackled with specialized DRL algorithms: Deep Deterministic Policy Gradient (DDPG) for continuous control and DQL for discrete scheduling, to ensure improved performance. The approach effectively tackles energy constraints for both UAVs and sensors, particularly in dynamic, obstacle-prone environments. Simulation results show the framework's effectiveness with significant energy savings and adaptability over conventional methods. Similarly, Ramadan et al. [42] investigated non-intrusive load monitoring (NILM) combined with IoT technologies to improve EE in

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residential settings. Using a Factorial Hidden Markov Model (FHMM), they disaggregated household electricity consumption by appliance from a single measurement point. Integrated with ThingSpeak for real-time visualization and Twitter alerts, the system outperformed combinatorial optimization (CO) in appliance-level prediction, achieving lower RMSE values. It also facilitates consumer load-shifting based on ToU pricing. Hafshejani et al. [43] equally suggested Signal-Dependent Sampling (SDS) to reduce IoT cyber-physical system (CPS) energy use. Unlike uniform sampling, SDS dynamically adjusts based on signal activity, achieving up to 94% power reduction with minimal precision loss. Case studies in ECG and greenhouse monitoring confirm the method's effectiveness in environmental applications, though ECG signals require careful tuning for diagnostic reliability.

Table 5. Summary of AI-driven software-based EE methods with EC and DSEM

Ref	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
[39]	VNF orchestration in UAV-MEC for smart farming	Distributed learning for resource efficiency	UAVs, MEC servers, IoT nodes	UAV agents use AFDQN; a decentralized setup	AoI, energy, robustness	AoI <200ms; better EE vs. centralized model	Fixed power/bandwidth; scalability untested
[40]	EE resource allocation for FL	Computation-communication balancing, parallelism	IoT clients, UAVs, OFDMA subchannels	Offline/online scheduling, bisection search	Energy, accuracy, workload balance	–25% energy, +40% accuracy vs. baseline	Complex computation; no real-world deployment
[41]	Reduce total energy use of UAVs and sensors during data collection while ensuring task completion	DRL-based trajectory planning, transmit power control, multi-UAV scheduling	UAVs (mobility, collection), sensors (data sources), DRL agents	DDPG (trajectory, power); DQL (scheduling); finite-horizon MDP	Energy consumption, success rate, DRL convergence, task allocation	90.8% success; adaptive power more efficient; near-optimal scheduling	No interference model; fixed altitude; simplified battery; limited environmental dynamics
[42]	Residential EE via NILM & IoT alerts	Load disaggregation, behavioural demand response	Smart meters, FHMM, ThingSpeak	FHMM on REDD dataset; real-time alerts	RMSE, responsiveness, load shift	FHMM RMSE: 37.6W vs. CO 49.46W; peak load cut	Limited validation; low-frequency data limits accuracy
[43]	Lower IoT CPS power usage	Rate adjustment based on signal features	ECG, greenhouse monitors	Bottom-up, software-only sampling control	Sampling, energy use, regen. error, accuracy	94% energy saved; minor accuracy impact	Needs careful tuning for complex signals

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5) Network-based Methods

This subsection discusses the studies that focused on network and communication optimization techniques to enhance EE in IoT systems. These techniques reduce communication overhead, refine routing protocols, and minimize energy-intensive network operations. Some studies employing these methods as standalone EE schemes are summarized in Table 6. Al-Sammak et al. [44] introduced an adaptive transmission algorithm for IoT-based smart meters which dynamically adjust transmission intervals based on real-time electrical variations. Implemented on Arduino prototypes with LoRaWAN and NB-IoT, it achieved an 86.81% reduction in packet transmissions and over 87% energy savings, validated through paired T-tests. The method enhances network stability but is sensitive to threshold value selection. Likewise, Wei et al. [45] proposed an over-the-air (OTA) update mechanism for DL models in low-power EH IoT devices, addressing intermittent power and communication constraints. Their approach integrates delta encoding for weight-change transmission, an energy-aware communication protocol, and runtime mechanisms for stable updates under power fluctuations. Tested on a TI-MSP430FR5994 device with BLE and a Raspberry Pi 4 edge server, it demonstrated a 7.3% reduction in update size, 25–30% energy savings, and a 45% improvement in update completion. Also, Duy et al. [46] developed EEGT, a grid-based routing protocol to improve energy distribution and hierarchical communication in WSNs. Utilizing multi-criteria CH node (CHN) selection, minimum spanning tree (MST) based intra-cell routing, and ACO-driven inter-cell routing, it optimizes transmission energy costs. While simulations indicate efficiency gains, the complexity of hybrid routing and the absence of hardware validation may limit the actual deployment.

6) Network-based Optimized with AI-driven Methods

This subsection discusses studies that optimized network approaches with AI-based methods while incorporating security and fault tolerance, as summarized in Table 6. Gang et al. [47] proposed an energy-efficient MAC protocol for UWSNs using Q-learning-based RL to mitigate collisions and extend network lifespan. Rx nodes dynamically adapt transmission strategies based on local observations, interference, battery status, and collisions, without requiring explicit coordination. Simulations show improved throughput, 38% fewer collisions, reduced energy use, and enhanced delay performance over standard MAC protocols. In parallel, Venkatachalam et al. [48] developed EEGP-MAC, a hybrid multi-agent MAC protocol integrating Q-learning and the Honey Badger Algorithm (HBA) for adaptive resource management. Their group-based prioritization scheme classifies nodes by location, energy level, and traffic type, assigning transmission priorities dynamically. Within each group, the QL-HBA algorithm selects optimal contending nodes using a fitness function based on local traffic and

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neighbourhood density. NS-3 simulations confirm EEGP-MAC outperforms IEEE 802.15.4, Hybrid-MAC, and QL-DGMAC in delay, energy efficiency, throughput, and packet delivery. Sellami et al. [49] focused on energy-aware task scheduling and offloading in 5G IoT edge networks using Deep RL (DRL) with an Asynchronous Actor-Critic Agent algorithm (A3C), SDN, and blockchain. The A3C algorithm optimizes task scheduling, while Proof-of-Authority (PoA) consensus secures communications, balancing computational load across edge and fog nodes. Simulations show reductions in energy consumption and processing delays, along with increased transaction throughput compared to PBFT. However, blockchain integration presents a complexity, with potential scalability and privacy concerns.

In a similar study, Singh et al. [50] proposed a six-tier smart parking framework integrating RSU-based blockchain for data authentication, ECC for secure communication, virtualization for efficient storage, and Deep LSTM for parking data analysis and recommendations. In addressing issues such as centralization, bandwidth constraints, and privacy risks, simulations show improved EE, data privacy, integrity, and availability. Abdi et al. [51] equally developed RLBEEP, an RL-driven protocol optimizing routing, sleep scheduling, and transmission restriction to extend the WSN lifespan. RL allows nodes to acquire energy-efficient policies based on residual energy, hop count, and distance, while sleep scheduling and transmission control minimize unnecessary consumption. Simulations show enhanced network lifetime compared to other RL-based protocols, though high computational demands at the sink node limit scalability in resource-constrained environments. Yugank et al. [52] in their study focused on ANN-driven duty cycle optimization for battery-constrained Systems-on-Chip (SoCs) in data communication.

They analyse operational parameters like duty cycle and power usage which are used by the ANN model to predict optimal power states, balancing energy during transmissions. The model was trained using a Scaled Conjugate Gradient (SCG) and evaluated with Mean Square Error (MSE). Experimental results show that a 40%-50% duty cycle threshold maximizes efficiency, offering a practical way to reduce energy used in real-time deployments. Furthermore, Javadpour et al. [53] suggested a distributed routing protocol incorporating fuzzy clustering and PSO for energy-aware load balancing in IoT-based WSNs. The method utilizes Fuzzy C-Means clustering for sensor grouping and PSO for optimal CH selection, enhancing the stability and computational efficiency in routing. NS-2 simulations indicate a 9.57% increase in throughput and an 8.47% reduction in energy use compared to existing protocols.

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Table 6. Summary of network-based and AI-driven EE methods

Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Key Results	Limitations
[44]	Adaptive transmission in IoT meters	Real-time scheduling via LPWAN (LoRaWAN, NB-IoT)	Smart gas/water meters with LPWAN	Microcontroller-driven adaptive transmission	Packet count, reliability	88.5% reduction in energy spikes	Scalability and security not analyzed
[45]	EE OTA DL model updates	Compression, energy-aware transmission	Edge server (RPi 4), TI-MSP430FR5994, LeNet-5	Real-hardware OTA updates	Update size, energy, robustness	7.3% smaller updates, 25–30% energy savings	Needs tuning; scalability unclear
[46]	Optimize WSN lifespan	Dynamic CHN selection, ACO routing	Sensor nodes, grid clusters	MST intra-cell, ACO inter-cell	Energy, uptime, harvested energy	+30% efficiency over LEACH-C	No hardware test; routing complexity
[47]	EE MAC protocol with RL for UWSNs	Adaptive TX power, collision avoidance	UWSN: CHs, Rx nodes, sink	Q-learning for slot scheduling	Throughput, delay, PDR, utilization	+23% throughput, –38% collisions	Needs large training data; static nodes; no real validation
[48]	EE MAC for large-scale IoT	Hybrid Q-learning with HBA	Grouped IoT devices (by energy/location/traffic)	Priority-based hybrid contention strategy	Delay, energy, PDR, throughput	45% energy cut, 10% PDR gain	Algorithm complexity; simulation-only
[49]	Energy-aware offloading in 5G IoT	DRL scheduling, PoA Blockchain security	IoT devices, fog nodes, SDN, Blockchain	DRL offloading, PoA Blockchain comparison	Latency, throughput, energy	Lowest latency (8.3s); 6M txns (vs. 5M PBFT)	Blockchain overhead; complex real deployment
[50]	EE smart parking with security	Virtualization, ECC, DL-based prediction	Sensors, RSUs, VMs, Blockchain nodes	ECC encryption, LSTM prediction	Energy, time cost, accuracy, privacy	Virtualization boosts EE; secure authentication	Scalability, real EE impact untested
[51]	Prolong WSN life with RL	Sleep scheduling, adaptive control	Sensor nodes, sink	RL reward-based sleep scheduling	Energy, signal accuracy, overhead	Delays FND by 25–35%, reduces energy	High compute demand; slow convergence
[52]	ANN for IoT power modeling	Duty cycle tuning, ANN power prediction	IoT sensors, SoCs, transceivers	MATLAB simulation	MSE, duty %, power usage	~50% duty cycle; accurate power modeling	No hardware validation

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Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Key Results	Limitations
[53]	EE & longevity in WSIoT	Fuzzy clustering, heuristic routing	CH, routing protocols	Two-phase: FCM for clustering, PSO for CH	Throughput, delay, energy, delivery rate	+9.57% throughput, –8.47% energy	No mobility support: cluster imbalance ignored

7) Network-based Optimized with Software-based Methods

A hybrid approach to improving EE in IoT systems that integrates software-based and network-based techniques is discussed in this subsection. While the software methods adjust energy usage in real-time, network-based approaches optimize communication overhead via energy-aware routing and EC. This combination reduces energy waste, improves connectivity, extends device lifespan, and supports sustainable smart grids. Key studies are summarized in Tables 7 and 8. dos Anjos et al. [54] presented a Time and Energy Minimization Scheduler (TEMS), a dynamic task scheduling algorithm with DVFS adaptation for hybrid IoT computing environments. Guided by a detailed cost model like processing energy, transmission energy, and device battery levels, TEMS facilitates balanced task allocation across IoT devices, MEC servers, and cloud centres. Simulations show energy savings of up to 51.6% and a task completion improvement of 86.6%, addressing growing IoT latency and energy challenges. Similarly, Ansere et al. [55] optimized the radio subsystem in large-scale 6G-enabled IoT networks through the Joint Energy-Efficient Resource Allocation (JEERA) algorithm. It jointly improves power allocation, sub-channel assignment, user selection, and active remote radio units (RRUs). The NP-hard optimization problem is tackled using fractional programming, Lagrangian decomposition, and the Kuhn–Munkres (KM) algorithm. Simulations demonstrate EE improvements of 33–37%, making JEERA a strong candidate for next-generation IoT systems. Furthermore, Ciuffoletti [56] proposed a remote checkpointing mechanism to support deep-sleep duty cycles in stateful IoT edge devices, preserving volatile memory across sleep cycles. Their technology-agnostic model compares energy costs against light sleep methods, identifying scenarios where checkpointing is more efficient. Additionally, a secure transfer and recovery protocol reduces security risks using dynamic identifiers. Hardware prototypes validate functionality and energy savings, highlighting the method's potential for constrained edge devices in low-duty-cycle, data-intensive applications.

Equally, Baniata et al. [57] developed MIMO-HC, a clustering protocol for MIMO-enabled IoT systems in 5G+ environments to tackle energy constraints, uneven depletion, and hotspot issues. Their centralized CH selection and unequal clustering strategy optimize cluster radii: smaller near the central station to reduce collisions, and larger for distant clusters to minimize delay. A probabilistic multi-hop routing system balances load among CHs, while interface selection enhances

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communication energy efficiency. Simulations show MIMO-HC outperforms UN-LEACH, achieving 3x longer network lifetime, 40% lower CH energy use, better load balancing, and improved stability. Hemanand et al. [58] also investigated energy-efficient communication protocols for smart city IoT using NB-IoT over LTE-M with an application server. Their framework assesses adaptive power control, duty cycling, data aggregation, protocol optimization, and network topology adjustments. Simulations indicate 15–25% energy savings, with adaptive power control and network topology optimization having the highest impact. In another study, Somula et al. [59] developed SWARAM, a CH selection protocol integrating Euclidean distance-based clustering with the bio-inspired Osprey Optimization Algorithm (OOA). Using a fitness function incorporating residual energy and base station distance, SWARAM optimizes clustering to balance energy use and prevent network energy holes. MATLAB simulations show it outperforms EECHS-ARO, HSWO, and EECHIGWO, achieving 78% higher packet delivery and 24% reduced energy consumption, demonstrating effectiveness in static WSN deployments. Also, Shilpa et al. [60] suggested a hybrid clustering and routing scheme for heterogeneous WSNs, combining dynamic/static clustering (EEHCT) with firefly optimization (FFO) for residual energy-aware clustering and route selection. Simulations demonstrate improvements in network lifespan and packet delivery, although inconsistencies in energy balance metrics and reporting reduce clarity.

Table 7. Summary of network-based optimized software-based EE methods

Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
[54]	Hybrid task offloading in IoT	Real-time workload-aware scheduling	IoT devices, MEC, cloud	3-layer offloading with DVFS	Energy, execution time	51.6% energy savings; 86.6% faster execution	Assumes static network performance
[55]	EE in dense 6G IoT	Power/subchannel/user/RRU optimization	6G RRUs, IoT radios	JEERA algorithm; convex optimization	EE, complexity	33–37% better EE, reduced complexity	Channel assumption complexity; no real validation
[56]	Remote checkpointing for energy saving	Software checkpointing for memory preservation	IoT edge with volatile memory	RPi + ESP8266 prototype	Energy vs. standby memory	Lower energy vs local standby	Network overhead can limit gains

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Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
[57]	EE routing for MIMO IoT in 5G	Unequal clustering, probabilistic multi-hop routing	MIMO-enabled WSN	CH selection, adaptive topology	Lifetime, energy, delay, balance	3× lifetime, –40% CH energy	Simulation only; scalability concerns
[58]	EE comms for smart city IoT	Duty cycling, power control, aggregation	NB-IoT, LTE-M, App server	Active/sleep modes, protocol optimization	Energy use, duty cycle	15–25% lower energy, 25% via power control	Scalability not addressed; partial validation
[59]	EE CH selection for IoT-WSN	Bio-inspired CH selection by residual energy & distance	Sensor nodes, CHs, Sink	Two-phase: distance clustering, OOA CH election	Lifetime, energy, PDR, overhead	24% energy cut; 78% more PDR	Simulation only; static nodes; no security
[60]	EE & longevity in HWSNs	Hybrid clustering with FFO	Heterogeneous sensor network	LEACH-style clustering + fuzzy logic routing	Lifetime, energy, loss, delay	90.27% lifetime improvement	No real validation; metrics unclear
[61]	Compression for longer IoT device life	Lossless data compression (S-LZW, S-LEC)	Cloud-based IoT sensing system	MILP to minimize energy & latency	Energy, lifetime, traffic	40% energy savings; 50% longer lifetime	Overhead not analyzed; scalability limited

Al-Kadhim and Al-Raweshidy [61] suggested an adaptive data compression scheme (ADCS) for cloud-based IoT networks to reduce transmitted data volume. It dynamically selects between Sensor Lempel-Ziv-Welch (S-LZW) and Sequential Lossless Entropy Compression (S-LEC) based on device processing capacity, battery level, and compression energy cost. Optimized to reduce power consumption in radio transmission and circuitry, simulations from a smart building setup show up to 40% power savings and a 50% increase in device lifetime compared to non-compression systems. Similarly, Memon et al. [62] presented the Energy-Efficient Fuzzy Management (EEFM) system, combining fuzzy logic with IoT-enabled VANETs to improve clustering efficiency. The routing algorithm applies fuzzy clustering with multi-hop communication and reduced beacon messaging. CH selection and packet rebroadcasting use fuzzy logic parameters like node distance, residual energy, neighbour count, traffic density, and packet redundancy. NS-2 simulations confirm superior energy use, lower delay, improved packet delivery, reduced control overhead, and extended network lifetime

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compared to existing fuzzy-based approaches. In the same vein, Abdulzahra et al. [63] introduced the Energy-Efficient Fuzzy-Based Unequal Clustering with Sleep Scheduling (EFUCSS) protocol for IoT-based WSNs. Combining unequal clustering for balanced energy distribution, fuzzy logic for CH selection, and sleep scheduling to deactivate idle nodes, the protocol adapts to different node distributions and base station distances. Simulations show EFUCSS outperforms existing methods in energy efficiency and operational duration, making it a practical solution for remote deployments.

Moreover, Merah et al. [64] proposed ESOM, an energy-efficient clustering protocol for IoT networks integrating self-organizing maps (SOM) with dynamic CH rotation. ESOM forms static clusters, initially selecting CHs based on proximity to the winning neuron, then rotating CHs in later rounds using residual energy and distance metrics to balance energy use and extend network lifespan. Simulations show ESOM outperforms LEACH-SOM in energy efficiency, though further research on multi-hop routing and collision avoidance could enhance performance. Similarly, Arafat [65] developed DECR, a distributed energy-efficient clustering and routing protocol for Wearable IoT-enabled WBANs for interference, user mobility, and battery constraints. It employs a two-hop neighbour-based clustering strategy and a modified GWO (MGWO) algorithm for CH selection and optimized routing. Additionally, an analytical model ensures balanced energy use through cluster sizing. Simulations indicate superior energy efficiency, network lifetime, and data reliability over MT-MAC and ALOC, demonstrating its suitability for dynamic health monitoring. Liu et al. [66] also presented EEGNBR, a routing protocol for UWSNs that eliminates node localization by using a distance-vector approach for efficient sink node paths. In the method, a concurrent relay selection mechanism enables multi-hop routing to reduce delays and ensure reliable transmission under mobility and communication challenges while conserving energy. Simulations show EEGNBR improves packet delivery ratio and end-to-end delay, with energy efficiency on par or better than existing protocols. Equally, Yao et al. [67] developed EERPMS, an energy-efficient clustering protocol for WSNs in precision agriculture. It applies multi-threshold image segmentation based on the Otsu algorithm, alongside a CH selection method considering residual energy and proximity to optimal locations. These techniques improve load distribution and network longevity. Simulations confirm lower energy use and extended network lifetime compared to RLEACH, CRPFCM, and FIGWO, reinforcing its viability for smart farming applications.

Mohamed et al. [68] presented LO-Dedup, a low-overhead inline deduplication method to reduce energy use in Green IoT systems by eliminating redundant wireless transmissions. Using hashed fingerprints, LO-Dedup detects duplicate sensor data chunks and transmits only indices, reducing data size and power consumption. Experiments with Arduino and Raspberry Pi confirm significant

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energy savings, especially for minimally varying sensor data, supporting real-time, energy-constrained IoT applications. In the same vein, Dogra et al. [69] suggested IMIMO-5G BEE, a routing and clustering protocol for IoT-enabled 5G WSNs using MIMO technology. It integrates hybrid clustering: single-hop and multi-hop communication, with CH selection via k-means clustering and a dynamic competition radius. An adaptive transmission interface mechanism optimizes energy utilization and quality of experience for various data types. Simulation results show a 30% energy reduction, extended network lifetime, improved coverage, and lower transmission delay compared to existing methods. Still on clustering, Mir et al. [70] developed DCOPA, a metaheuristic-driven distributed clustering protocol for IoT-based WSNs employing multiple-criteria decision-making (MCDM) for CH selection, considering residual node energy and base station distance. Nodes self-elect as CHs using a timer weighted by these criteria, ensuring balanced energy use and optimized clustering radius. Simulations confirm superior energy efficiency, extended network lifetime, and enhanced scalability over LEACH and related protocols. In addition, Malik and Kushwah [71] presented EES-IA, a hybrid cross-technology communication protocol for IoT networks operating in the 2.4 GHz spectrum. ZigBee handles low-power control and wake-up signalling, while Wi-Fi ensures reliable data transmission. The system employs an Interference Avoidance (IA) algorithm based on packet error rate and link quality. Omnet++ simulations show that EES-IA reduces energy use and interference while improving throughput compared to Green IoT Gateway.

Table 8. Summary of network-based optimized software-based EE methods

Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
[62]	EE, lifetime & QoS in VANETs	Fuzzy CH selection, multi-hop routing	VANET with IoT	Density-based rebroadcasting; fuzzy CH selection	Lifetime, PDR, QoS	Improved lifetime, throughput, lower delay	High routing load at high speeds; fuzzy rule complexity; highway-only test
[63]	Extend IoT lifetime via clustering	Unequal clusters, fuzzy CH, duty cycling	Sensor nodes, CHs, gateway, BS	Python sim; fuzzy-based clustering	Lifetime, energy, balance	39.6%–408.1% lifetime gain, less redundancy	Assumes static, homogeneous nodes; ignores interference
[64]	EE & lifetime via SOM clustering	Static clustering, dynamic CH	IoT nodes, CHs, BS	LEACH-based sim, varied distributions	Energy, cluster quality, lifetime	Better energy use vs LEACH-SOM;	Static initial clustering, single hop only; no deployment

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Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
						balanced, stable	
[65]	EE clustering & routing for WBAN	Adaptive clustering, routing optimization	Wearable IoT, CHs, sink	Compared to MT-MAC & ALOC	PDR, delay, energy, overhead	Higher PDR, lower delay, better energy use	Initial info overhead; no real deployment
[66]	Routing for UWSNs (no localization)	Adaptive routing, forwarding protection	UW sensor nodes, sinks	GUIDE routing (timeless forwarding)	Delay, PDR, energy, lifetime	Outperforms DBR, DVOR; lower delay	Relay selection complex; updating under mobility
[67]	EE routing for agriculture WSNs	Residual-energy-aware clustering	Sensor nodes, BS	Energy model + CH selection	Energy, lifetime, load balance	64.5% energy savings; 57% longer FDN lifetime	Static BS; may not scale well computationally
[68]	Reduce IoT transmission energy	Inline data deduplication	WSN, gateway, metadata server	JSON deduplication prototype	Size, power	56B→8B; 1.808W→ 1.793W	Small hardware scale; no multi-sensor test
[69]	Routing for IoT w/ 5G & MIMO	MIMO-optimized clustering, energy-aware routing	IoT nodes, BS, MIMO devices	NS-3 sim; cluster + QoE routing	Energy, delay, QoE, coverage	30% less energy, better lifetime	No security; interface selection complexity
[70]	Distributed EE clustering for WSN	Energy-balanced clustering	Sensor nodes, BS	Timer-based CH; optimized scheduling	Energy, lifetime, CH election	LND 1272 vs. 1055 (LEACH); less energy used	No real validation; timer complexity
[71]	EE scheduling for multi-radio IoT	Interference-aware, mixed proactive/reactive	IoT with ZigBee/Wi-Fi, gateways	Omnet++ sim (30 nodes)	Energy, PER, BER, throughput	Lower energy, fewer errors, more	Stationary gateway; no PHY-layer tests

Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
						throughput	

8) Network-Software-based Optimized with Edge Computing and Security

This subsection explores the intersection of software-based techniques, network optimization, and EC to improve EE in IoT systems. While these smart algorithms dynamically adjust power use, optimized networks reduce unnecessary communication, and local data processing minimizes delays and cloud dependence, with integrated security where needed. Tables 9 and 10 summarize the important studies. Algarni et al. [72] suggested a two-level distributed EC architecture addressing scalability, latency, and EE challenges in dense IoT networks. Integrating fog computing and multi-access EC (MEC), allows dynamic task offloading from resource-constrained devices to nearby fog nodes or MEC servers. By using the Salp swarm optimizer (SSO) for resource allocation, it balances computational and communication loads to reduce energy consumption and latency. Experimental validation on a real IoT testbed confirms superior performance over traditional IoT networks, though mobility effects remain a challenge. Periasamy et al. [73] equally developed ERAM-EE, an energy-efficient algorithm for resource allocation and management in fog-enabled IoT networks. Fog computing decentralizes processing, reducing latency and enhancing responsiveness. ERAM-EE tackles energy constraints, uneven traffic loads, and unstable wireless connections. Using a channel gain matrix, it assigns IoT devices to fog nodes (FNs) via resource blocks (RBs), optimizing task offloading and energy use while avoiding congestion. Simulations confirm its superiority over OR-EPA, RR-OPA, and EE-CN in energy savings and speed.

Feng et al. [74] presented a collaborative offloading strategy for IoT systems using NOMA-enabled fog computing, employing mixed-integer nonlinear programming (MINLP) to minimize total energy use while meeting delay constraints. Tasks are loaded to pairs of fog nodes using NOMA for simultaneous transmission, reducing the overall energy costs. The problem is split into fog node selection: handled via a weighted bipartite graph and the Hungarian algorithm, and resource allocation, addressed through convex reformulation with the MCTC algorithm. Simulations show MCTC outperforms OMA, and NOMA without pairing, and full offloading, achieving up to 85% energy savings. Similarly, Liu et al. [75] optimized EE in UAV-based IoT networks lacking ground infrastructure, proposing a resource optimization framework for multi-UAV systems where UAVs serve as aerial base stations. The framework maximizes minimum EE by jointly optimizing communication scheduling, power allocation, and flight paths. Due to the non-

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convex nature of the issue, it is decomposed into three sub-problems and solved iteratively using the Dinkelbach method and subsequent convex approximation. Simulations show improved EE, balanced UAV energy distribution, and enhanced network sustainability and fairness. On the same note, Wu et al. [76] presented DAEE, an online task offloading algorithm for delay-sensitive and compute-intensive (DSCI) tasks in IIoT systems using MEC. They formulated the offloading problem via perturbed Lyapunov optimization to minimize long-term energy use while maintaining task deadlines. Additionally, virtual queue management dynamically adjusts offloading decisions based on network state and backlog data. Simulations demonstrate superior EE and latency control compared to greedy energy-saving approaches, particularly under high workload and mobility conditions.

Table 9. Summary of network-software-based methods optimized with EC & security

Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
[72]	Efficient resource allocation in dense IoT	Hierarchical task offloading, dynamic energy use	IoT end devices, fog nodes, MEC servers	Multi-tier optimization via SSO	Energy use, latency, congestion reduction	19% energy savings, 86% latency reduction	Mobility effects not fully studied
[73]	Maximize EE in Fog-IoT networks	Energy-aware task offloading, resource balancing	IoT devices, Fog Nodes, RBs, channel matrix	Simulated evaluation vs. OR-EPA, RR-OPA, EE-CN	Efficiency (bit/J), response time, utilization, complexity	Up to 18 Mbit/J efficiency gain; reduced processing time	Limited dynamic IoT device handling; memory constraints
[74]	Minimize energy in IoT via collaborative offloading	Joint offloading optimization using NOMA & TDMA	IoT task nodes, fog nodes, CPUs	MCTC algorithm for fog selection & resource allocation	Total energy use, latency, task size, computation cycles	56.88%-84.78% lower energy vs baseline	Assumes ideal CSI/SIC; limited scalability in dynamic networks
[75]	Maximize UAV EE via trajectory & scheduling optimization	Joint communication scheduling & UAV trajectory planning	Multi-UAVs as base stations, ground IoT nodes	Successive convex approximation	UAV energy use, fairness, throughput	Improved fairness & EE	Assumes ideal LoS; lacks real-world tests; computationally complex

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Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
[76]	Optimize MEC energy use for delay-sensitive IIoT tasks	Dynamic scheduling, network-aware offloading	IIoT devices, wireless links, MEC servers	Mobility-aware optimization framework	Energy, queue stability, delay guarantees	Outperforms greedy schemes; adaptive to workload changes	Single edge server assumed; no real-world validation
[77]	Improve EE and security in MFBC for IoT	DVFS, energy-aware scheduling, EC, lightweight algorithms	Energy model, job/VM scheduling, blockchain	Java simulation on IBM z13 (2200 VMs, 40 servers)	Energy use, latency, throughput, attack detection	379.5J vs 427J+ energy; 0.165s vs 0.172s+ latency	Less optimal for small packets; blockchain overhead

Beyond software and network optimization, security and reliability are also integrated to enhance EE. Key studies in this domain are summarized in Table 9. Razaque et al. [77] proposed EESH, a hybrid algorithm for mobile fog-based cloud (MFBC) IoT systems, combining voltage scaling for energy savings with blockchain-based malicious data detection (MDD). The algorithm utilizes energy estimation, task scheduling, and parallel processing to optimize resource utilization. Simulations under varied workloads show improved EE, latency, and security by effectively identifying malicious data blocks. Accordingly, Salim et al. [78] developed SEEDGT, a secure and energy-efficient data-gathering technique for IoT-based WSNs. It integrates trust-based clustering, homomorphic encryption for secure aggregation, and a modified compressive sensing (CS) method to minimize data volume and energy use. Operating in three phases: cluster formation, network operation, and reconfiguration, it strengthens security while adaptive compression reduces communication overhead. Simulations demonstrate increased network lifetime and EE, along with strong security protections. Likewise, Philip and Singh [79] developed TPSS, an adaptive LoRaWAN-based communication protocol for dynamic water monitoring applications. It extends battery life by adjusting transmit power and spreading factor based on node distance. Their study also includes carbon footprint analysis, validated through analytical modelling and real-world testing. Results indicate that 62% of energy savings near gateways and an 8.6 kg per node reduction in carbon emissions while maintaining communication reliability.

Sankaran and Kim [80] proposed a secure, energy-efficient data transmission framework for IIoT, managing complex, large-scale sensor data. It combines multi-scale grasshopper optimization (GOA) and robust multi-cascaded CNN (RMC-CNN) for anomaly detection, it employs a dynamic honeypot-based encryption algorithm (DHEA) for data security and blockchain for decentralized key management. Experiments confirm superior accuracy, throughput, latency, and attack detection compared to existing methods. Nagaraju et al. [81] equally suggested a unified protocol for heterogeneous IoT-enabled WSNs, tackling EE, security, and data management. It combines secure multipath routing (MLRP), energy optimization with load balancing (H-TEEN), and enhanced data storage (U-DSP). NS-2 simulations show superior performance over LEACH, CCBRP, and PEGASIS, achieving a 25% reduction in end-to-end delay, 20% higher throughput, and a 35% increase in network lifetime, energy use, and storage capacity. In another study, Sharma et al. [82] proposed MHSEER, a meta-heuristic secure and energy-efficient routing protocol for WSNs in IIoT settings. It combines meta-heuristic routing with lightweight encryption using Counter-Encryption Mode (CEM). With this, routing decisions consider hop count, connection integrity, and residual energy, helping to manage node depletion and maintain stable communication. MATLAB simulations demonstrate 95.81% throughput, a 5.12% packet drop ratio, and low energy utilization, showing effective encryption and route maintenance.

Asaithambi et al. [83] tackled high energy use, single points of failure, and security gaps in traditional IIoT deployments. Their approach integrates decentralized blockchain for identity and data management with SDN for centralized control and traffic optimization, improving security and network efficiency. An energy-aware CH selection algorithm extends the device lifespan using residual energy metrics. Simulated using Mininet-WiFi and Vechain blockchain, results show enhanced throughput, reduced latency, and lower energy use compared to existing SDN models. Similarly, Swathi et al. [84] developed a unified system for EE and fault tolerance in IoT-enabled WSNs. Integrating the ANFIS Reptile Optimization Algorithm (AROA) for inter-cluster routing and Tuned Supervision-Based Fault Diagnosis (TSFD) for fault detection, it optimizes routing via a hybrid AROA-based Accessibility Index (AI) considering residual energy, response time, and node activity. MATLAB simulations show a 72% energy reduction, 52% extended network lifetime, and 97% fault detection accuracy.

Table 10. Summary of network-software-based methods Optimized with EC & security

Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
[78]	Secure & EE data gathering in IoT WSNs	Trust-based clustering, encrypted aggregation, adaptive compression	IoT sensors, CHs, BS	SEEDGT simulation with clustering	Network lifetime, energy per round, alive nodes	Extended lifetime with secure aggregation, reduced energy	No real-world validation; trust-weight tuning complexity
[79]	TPSS for dynamic LoRa	Adaptive transmit power &	LoRaWAN end-nodes,	Field tests in reservoir	Energy savings, reliability,	62% energy savings near gateway; 38%	Limited EH integration;

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Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
	nodes in water monitoring	spreading factor	gateway, water sensors		carbon footprint	far; carbon reduced 8.6 kg/node	environment sensitivity
[80]	EE & secure data transmission in IIoT	Energy-aware optimization, anomaly detection, secure encryption	IIoT sensors, optimization module, blockchain key storage	GOA optimization, RMC-CNN attack detection, dynamic encryption	Accuracy, precision, recall, throughput, latency	RMC-CNN 99.2% accuracy; encryption improves security & Transmission	Limited real-time validation; encryption complexity issues
[81]	Secure EE routing for heterogeneous WSNs	Secure routing, hybrid clustering, distributed storage	Heterogeneous sensors, BS, IoT sources	Multipath routing, Hybrid-TEEN clustering, U-DSP storage	Delay, throughput, energy, lifetime, storage	25% delay reduction; 20% throughput gain; 35% lifetime extension	Protocol complexity; no real-world validation
[82]	EE & secure routing for IIoT WSNs	Optimized routing, lightweight encryption	IIoT sensor nodes, BS, encrypted routing modules	MATLAB simulation of routing & Encryption	Throughput, PDR, delay, energy, faulty paths	95.81% throughput; 5.12% PDR; 0.10 ms delay	Limited real-world validation; compatibility concerns
[84]	EE inter-cluster routing & fault management	AI-based adaptive routing & fault tolerance	Cluster leaders, members, sink, fault modules	MATLAB sim (1000 nodes)	Energy intake, lifetime, stability, forwarding time, accuracy	72% energy intake reduction; 52% lifetime extension; 97% fault detection	Strong integration; lacks real deployment
[83]	EE & secure SDN for IIoT networks	CH selection via SDN energy optimization	SDN controllers, IoT devices, blockchain ledger	Mininet-WiFi emulator; Vechain blockchain	Energy use, latency, throughput	Reduced energy, latency; improved throughput	Simulation-based; blockchain overhead untested

9) Network-software-based Methods with DSEM

This hybrid technique integrates network optimization with DSEM to enhance EE by aligning consumption with real-time grid conditions while ensuring reliable, low-latency communication. DSEM reduces peak demand and supports adaptive energy use, while network optimization minimizes communication overhead for efficient data exchange. Table 11 provides a summary of the important studies. Ali et al. [85] developed REEFSM, a reliable and energy-efficient framework with sink mobility for UWSNs to deal with energy constraints and unreliable data

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transmission. The system utilizes a segmented network architecture with strategically placed mobile sinks, reducing redundant data forwarding, and optimizing sensor activity and communication. Additionally, adaptive duty cycling, neighbour discovery, and intelligent packet forwarding improve efficiency. Simulations show REEFSM outperforms EERBCR and DEADS, reducing energy use by up to 43%, improving data reliability by 35%, and ensuring zero dead nodes with minimal packet loss. Equally, Yarinezhad et al. [86] proposed RTG, a routing protocol for green IoT networks using mobile sinks to improve EE, extend network lifetime, and reduce end-to-end delay. It focuses on low sensor node energy, hot-spot issues, and routing complexities from sink mobility. Accordingly, RTG divides the network into an inner zone using tree-based routing for fast updates and EE, and an outer zone with improved geographic routing for balanced energy use and prevent loops. Simulations confirm superior lifetime, throughput, and lower delay compared to existing protocols.

DSEM, a software-based technique, is integrated with AI-driven methods to dynamically adjust power usage, predict demand fluctuations, and optimize energy distribution. Table 10 summarizes key studies. Azizi et al. [87] addressed scheduling challenges for delay-sensitive, heterogeneous IoT tasks in fog computing environments with limited resources. They proposed two semi-greedy heuristic algorithms, Priority-aware Semi-Greedy (PSG) and PSG with Multistart (PSG-M), which prioritize tasks based on deadlines while estimating energy consumption to guide allocation. These methods minimize deadline violations without increasing energy use. Simulations confirm superior task completion and reduced violation times over existing approaches, showcasing the combined benefits of software-based energy management, EC, and DSEM. Hazra et al. [88] proposed EaDO, an energy-aware data offloading technique for IIoT sensor networks to deal with challenges in handling delay-sensitive emergency data. It combines fog computing with two strategies: Emergency-aware Scheduling (EaS) using a multilevel feedback queue for prioritization, and Energy-aware Offloading (EaO) utilizing Hall's theorem for optimal task allocation. The system reduces total energy use, queuing delays, and CO_2 emissions more effectively than existing methods while maintaining fair energy distribution through simulations.

Table 11. Summary of DSEM with Network-based and Software-based methods

Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
[85]	Address energy constraints and unreliable data in UWSNs	Mobile sink deployment, duty cycling, wake/sleep scheduling	Underwater sensor nodes, mobile sink regions	Horizontal mobile sink movement; optimized packet forwarding	Energy consumption, PDR, packet drop rate, network lifetime	43% lower energy use; 35% higher data reliability;	Discrepancies in packet drop data; limited sink mobility; no real-world validation

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Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
						zero dead nodes	
[86]	Energy-efficient routing to prolong IoT network lifetime with mobile sinks	Energy balancing via routing; mobile sink load distribution	IoT sensor nodes, mobile sink, routing mechanisms	Partitioning into InSection & OutSection; "Improved Geographic" and tree-based routing.	Network lifetime, delay, throughput, energy consumption	RTG achieved longest lifetime, highest throughput, lowest delay	Limited to single mobile sink; simulation-only evaluation
[87]	Minimize IoT task energy and meet deadlines in fog computing	Priority-aware scheduling balancing energy and deadlines	IoT devices, fog nodes, cloud infrastructure	MINLP modelling and heuristic implementations	Deadline satisfaction, violation time, energy use	97.6% reduction in deadline violation; optimized energy use	Assumes single task per fog node; lacks fault tolerance
[88]	Minimize energy and latency in industrial IoT data offloading	Fog computing offloading with emergency task prioritization	Industrial IoT sensors, fog/cloud nodes	Hall's theorem-based matching; queueing optimization	Queueing delay, energy use, CO2 emissions	23-30% lower energy use; improved fairness and CO2 reduction	Static task/device assumptions; complex real-time deployment

10) Hardware-based Methods Optimized with REI, Software, Network and AI Ap

This section presents another hybrid EE approach that integrates REI with energy-efficient hardware to build sustainable, resilient IoT energy systems. REI considers environmental impacts such as carbon emissions and fossil fuel dependency using solar, wind, and other clean sources. Hardware-based methods like low-power microcontrollers and EH sensors, minimize energy use, extend device lifespan, and support smart grids and IoT applications. Tables 12 and 13 summarize the important studies. Hnatiuc et al. [89] presented an autonomous solar-powered IoT system with LoRaWAN for vineyard monitoring. The low-cost setup combines renewable EH with hardware and software optimizations. Experimental results show that reducing GPS update frequency and enabling idle modes lowers energy use. Field tests confirm six days of autonomy without solar input, demonstrating its suitability for off-grid deployments. Similarly, Wang et al. [90] designed a low-power, battery-less sensor for Agri-IoT applications, integrating on-chip sensor

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fusion, RF EH, and event-driven BLE communication. Its SCMSS and DAFE circuits sense temperature, humidity, and soil moisture with just 4.8 μW power. Manufactured in 65-nm CMOS technology, the sensor eliminates battery replacements, reducing environmental impact. Simulations demonstrate reliable accuracy, making it viable for scalable smart agriculture. Shukla et al. [91] equally developed a unified framework combining processing-in-memory (PIM) with kinetic EH (KEH) for energy-efficient ML in IoT and edge devices. LUT-based in-memory computation minimizes data movement, while piezoelectric KEH provides intermittent power. Experimental results show that 8-bit fixed-point inference maintains accuracy while enhancing EE. Accordingly, Haroun et al. [98] designed a battery-less wireless sensor transmission unit (WSTx) powered by indoor solar EH. Using polycrystalline photovoltaic cells, MPPT-based PMU, and LoRa, the system enables efficient low-power operation. Firmware optimizations, including deep sleep cycles and sensor power management, extend operation under minimal lighting. However, supercapacitor self-discharge and limited sensor compatibility may affect adaptability.

Table 12. Summary of hardware-based optimisation with REI, Software, network, and AI

Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
[89]	Autonomous solar-powered IoT deployment in agriculture	Hardware (solar panel, battery, PWM controller); software optimization	Solar panel, PWM controller, battery, LoRaWAN nodes, Arduino	Real-world field deployment	Power consumption, autonomy, connectivity reliability	6.83 days autonomy; software optimization improved efficiency	Single application case; lacks adaptive load response
[90]	Low-power battery-less IoT sensor for agriculture	RF EH; event-driven BLE transmission	Capacitive sensors, shared DAFE, BLE, RF harvester	65-nm CMOS fabrication; BLE at 2.4 GHz	Power use, accuracy, BLE TX range, EH performance	Ultra-low power (4.8 μW); battery-less operation; accurate sensing	Short BLE range (12 m); dependency on 2.4 GHz RF sources
[91]	Reduce ML energy use on IoT/edge devices	PIM, KEH	LUT-based PIM cores, piezoelectric KEH devices	Fixed-point computation; CNN benchmarks	Energy consumption, packet rate, cluster energy deviation	1.9 mW KEH in 5 s; high inference efficiency	No hardware prototype; energy depends on motion
[92]	Energy-efficient protocol for large-scale IoT WSNs	Energy-aware routing, hardware EH,	Heterogeneous sensor nodes, zone aggregators, EH relay nodes	Hybrid offline-online threshold; MSWE heuristic optimization	Energy savings, lifetime, data transmission, complexity	29% energy savings, 68% lifetime extension, improved	Computational overhead; increased delay in large networks

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Ref.	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
		computation filtering				load balancing	
[93]	Secure energy-efficient communication in IoT	Battery-aware source selection, EH, secure jamming	IoT sensors, relays, destination node	Monte Carlo simulation; Markov analysis	Secrecy throughput, energy failure rate, stability	Higher secrecy & efficiency vs. traditional methods	Latency-security trade-off; complex node interactions

In terms of hardware-based methods and network optimization, while low-power processors and optimized sensors reduce device energy use, network optimization minimizes latency, redundant communication, and transmission overhead using energy-aware routing. Table 11 also provides a summary of key studies. Abdul-Qawy et al. [92] proposed TESEES, a reactive, energy-efficient protocol for large-scale, heterogeneous IoT-based WSNs. Building on SEES, it introduces a zone-based architecture with event-driven data reporting and transmission thresholds to reduce redundancy and conserve node energy. By joining a threshold-based minimum-cost cross-layer transmission (TMCCT) algorithm and energy-harvesting relay nodes, TESEES improves scalability and load balancing. Simulations confirm 29% energy savings, a 68% increase in network lifetime, and enhanced data handling, making it suitable for dense environments. Similarly, Gouissem et al. [93] focused secure and energy-efficient communication scheme for cooperative IoT networks, incorporating physical layer security, artificial jamming, and energy harvesting (EH). A battery-aware source selection mechanism optimizes energy use among relay nodes, while amplify-and-forward (AF) transmission with jamming protects against eavesdropping and supports EH at sensor nodes. Monte Carlo simulations and Markov analysis demonstrate improvements in secrecy capacity, EE, and system stability as more sources cooperate.

Furthermore, REI is combined with software-driven and network optimization methods to enhance EE, connectivity, and sustainability in IoT-driven energy systems. Table 11 provides a summary of key studies. Islam et al. [94] developed a framework for deep neural network (DNN) inference on EH devices to deal with power and computational constraints. It utilizes Low Energy Adaptation (LEA) to modify model complexity based on available power and Checkpoint-Free Intermittent (CLI) inference to preserve computational state across power failures with minimal energy use. A consistency-aware execution mechanism ensures correctness under intermittent conditions. Experiments on a low-power microcontroller confirm improved memory efficiency and reliable DNN inference where traditional methods fail. Kang and Lim [95] also proposed the Energy Intelligence Platform Module (EIPM) to mitigate solar-powered system challenges, particularly unpredictable ambient energy, and capacitor depletion. The lightweight

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software-hardware system manages EH in resource-constrained IoT devices via energy prediction, task scheduling, and state checkpoints. A two-state Markov model forecasts energy availability, dynamically adjusting task execution and selectively saving device states to reduce information loss. Simulations validate its effectiveness.

In another study, hybrid access points (H-APs) with renewable energy sources are suggested [96]. Cao et al. [96] introduced a joint optimization framework for improving EE in simultaneous wireless information and power transfer (SWIPT)-enabled IoT networks. To deal with intermittent power at H-APs and terminals, they devise a non-linear mixed-integer problem utilizing power allocation, time-switching, and energy cooperation among H-APs. Additionally, a two-stage solution applies iterative methods for power and time-switching and a many-to-many matching algorithm for energy sharing. Simulations confirm EE gains and reduced consumption, especially in dense environments, outperforming baseline and PSO-based models. Similarly, Bharathi et al. [97] developed EMEECP-IoT, an enhanced multitier energy-efficient clustering protocol for IoT-based WSNs, targeting EE, security, and network lifespan. It integrates a three-layer clustering architecture with wireless EH and a security mechanism for detecting rogue nodes. Clustering and routing decisions leverage PSO, while transmission power control and a lightweight encryption scheme (TBSA) minimize energy use. Simulations confirm a 37% increase in network lifespan, a 21% improvement in energy efficiency, and enhanced data throughput compared to existing techniques.

Table 13. Summary of hardware-based optimisation with REI, Software, network, and AI

Ref	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
[94]	Efficient DNN inference on energy-harvesting devices	Hardware energy adaptation; intermittent software execution	MSP430 MCU, custom DNNs, non-volatile FRAM memory	Ultra-low-power MCU implementation; memory-optimized DNNs	Inference latency, memory efficiency, inference success rate	1.65× lower latency; memory-efficient execution	Limited scalability; small DNN models only
[95]	Mitigate power depletion in EH-IoT devices	Predictive scheduling, checkpointing, capacitor voltage monitoring	Solar-powered wireless sensor node	Markov-based scheduling and task execution optimization	Task execution rate, power depletion events, uptime	93.4% fewer depletion events; 15.6× uptime increase	Increased execution latency; depends on prediction accuracy
[96]	Maximize energy efficiency with SWIPT &	SWIPT-enabled RF harvesting; smart grid	H-APs, IoT terminals, smart grid	Dinkelbach alternating iteration; many-to-many	Energy efficiency, consumption, convergence time	Outperforms PSO & rate-maximization; enables energy reuse	Assumes perfect CSI; relies on smart grid; lacks

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Ref	Objective	EE Techniques	System Components	Implementation / Approaches	Evaluation Metrics	Results	Limitations
	energy cooperation	energy cooperation		cooperation matching			economic trading model
[97]	Enhance energy efficiency & security in IoT WSNs	Clustering, power control, wireless EH, encryption	Three-layer cluster WSN with security integration	PSO for clustering/path optimization; TBSA encryption	Network lifetime, throughput, latency, packet loss	35% longer lifetime; 21% energy reduction	Ignores node mobility; complex multi-tier framework
[98]	Develop ultra-low-power WSN device	Solar harvesting; low-power firmware	Polycrystalline PV, MCU, LoRa module	MPPT power extraction; sensor sleep cycles	Power harvested, throughput, energy per inference, delay, accuracy	85.7% efficiency; ~6 hours continuous operation	Limited indoor harvested power; firmware complexity

3.2. Discussion And Future Directions

3.2.1. Discussion

EE is a critical factor in the development of IoT and WSNs since it extends network lifetime and influences operational costs and system reliability. This study analysed various EE techniques such as AI-based optimization, system-level strategies, clustering routing, secure transmission protocols, and hardware innovations. This is summarized in Tables 2 to 13. The findings are presented methodologically, performance-wise, and comparatively showing the important trade-offs and future research directions for optimising energy use in IoT ecosystems. We considered publications from 2021 to 2025 and presented the summary of the years in terms of journals and conference papers. As shown in Figure 4, research on energy-efficient IoT systems topped in 2022, particularly in journals indicating increased investment and technological progress. Journal output remains stable while conference publications fluctuated, peaking in 2023 and 2024 before a slight decline. The trends suggest a shift towards more in-depth studies in journals, with timely insights from conferences. During this period, advances in AI-based optimization, edge, and fog computing, and EH-supported sustainable IoT deployments. In addition, secure clustering, efficient routing, and blockchain-based security improved system trust and resilience. By 2025, although ongoing, research has turned to refining the methods of integrating hardware efficiency, software intelligence and network optimization to allow scalable, sustainable IoT infrastructures.

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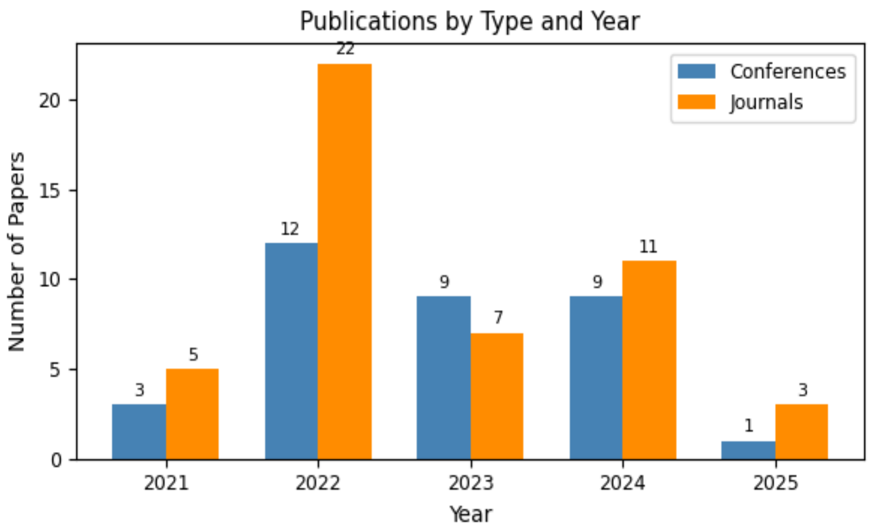

Figure 4. Publication trends

In terms of the findings, our analysis shows a growing trend towards integrated, multi-objective routing and cross-layer energy optimizations, with significant progress in minimizing energy use, network lifetime and improving security mechanisms. Figure 5 shows energy savings across randomly selected studies due to the proposed EE techniques. In particular, the analysis reveals that AI-based optimization enhances energy management in IoT and WSN through dynamic load forecasting, autonomous scheduling, and adaptive routing. Studies such as [22] and [23] employed multi-agent RL and transformer-based algorithms, achieving 40–60% energy savings in urban environments. Similarly, [26] utilized MDP smart routing but faced computational overhead in real-world deployments. Energy-aware RL protocols like Q-learning, explored in [24], [25], and [26], improved network lifetime and reduced packet loss in constrained IIoT and WSN settings. UAV-assisted decision-making using FL, as seen in [39] and [58], cut energy use by 25% while enhancing efficiency. Fuzzy logic and ANN-based optimization, adopted in [74] and [79], further reduced costs across various IoT applications. However, AI-based methods introduce computational overhead, rendering DRL impractical for low-power IoT due to processing demands. RL-based scheduling in [53] and [40] increases computational costs, while DRL approaches in [22] and [23] require significant memory and power. Simple rule-based methods, including those in [47] and [48], are less adaptive but effective in stable conditions. Despite advancements, high computational requirements, extensive training data reliance, and scalability challenges remain key barriers to AI-driven energy optimization in practice.

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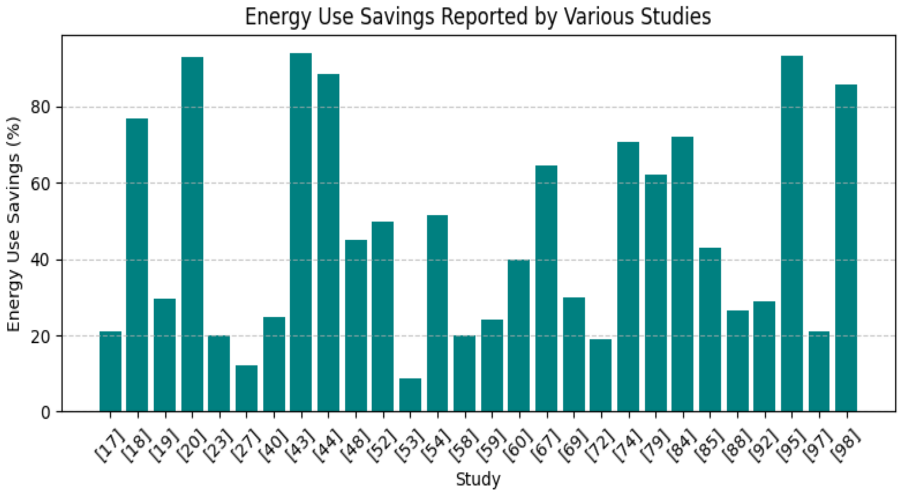

Figure 5. Energy savings across studies

System-level energy optimization in IoT relies on multi-layer techniques integrating offloading, compression, and security via blockchain to minimize energy use. Hierarchical offloading frameworks, such as those in [54] and [72], combine fog computing, MEC, and DVFS to dynamically balance computing loads, achieving 19–51.6% energy savings. These methods perform well in static environments but face challenges in dynamic networks. Data compression techniques in [18] and [21] improve transmission efficiency, with Huffman coding and lossless compression reducing energy costs by 77%. Edge-based federated learning (FL) [39], [40] enhances decentralized resource allocation, cutting transmission energy by 25%. Studies [19] and [20] integrate predictive security, blockchain, and hardware-aware controls, improving energy efficiency (EE) by ~29%. However, blockchain encryption adds processing costs and hierarchical frameworks require fine-tuning for optimal performance. While cross-layer optimizations enhance system stability, they introduce computational overhead and require careful deployment.

Moreover, communication-level strategies extend node lifetimes in IoT-based WSNs and underwater deployments [85], [86]. Duty cycling, transmit power control, and adaptive modulation are widely used, alongside clustering-based routing techniques that minimize redundant transmissions and optimize resources [86], [97]. Studies such as [32], [33], [52], [74], [76], employ metaheuristic and bio-inspired clustering algorithms, including GWO, MOA, FFO, DA, SSO, PSO, etc. to improve CH selection and EE, achieving a +333.51% stability improvement. Hybrid clustering frameworks in [53] and [59] combine fuzzy clustering with PSO to boost packet delivery but require scalability improvements. Self-organizing clustering mechanisms in [64] and [65] enhance packet delivery and reduce routing overhead. While these techniques outperform traditional methods like LEACH

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and PEGASIS, their reliance on static initial clustering poses challenges in mobile network setups.

In dynamic IoT environments like LoRaWAN and UWSNs, algorithms such as TPSS and REEFSM demonstrate that transmission control, mobility, and adaptive routing can achieve over 40% energy savings [85], [79]. However, packet drop variability and constrained node mobility remain underexplored. Multi-threshold CH selection routing algorithms like MDP, developed in [66] and [67], improve energy efficiency in precision agriculture and UWSNs, achieving 43% energy savings with reliable performance. In latency-sensitive IIoT applications, hybrid schemes integrating GOA with anomaly detection and encryption enhance accuracy, throughput, and EE [80]. Despite benefits, bio-inspired models require extensive tuning and adaptive clustering often incurs high processing costs, limiting deployment in low-power IoT networks. Future directions may involve ML-based cluster selection combined with lightweight heuristic routing.

Balancing data security with EE is another critical challenge. Blockchain-based security models, such as [83], integrate SDN and decentralized trust mechanisms to improve EE by 35% while enhancing latency and efficiency. Studies like [77], [78], and [81] use homomorphic encryption and multipath secure routing to prevent data leakage while minimizing energy waste, though encryption overhead increases costs. Adaptive cryptographic compression techniques [82], [51] improve energy use by 30% but offer weaker encryption compared to blockchain-based methods. Blockchain models provide stronger security but at higher energy costs, whereas lightweight cryptographic methods save power but require optimization for sensitive contexts.

Battery-less designs and EH offer sustained IoT operation without traditional energy sources. Studies in [89], [90], [96], and [98] explore solar, RF, and KEH for agricultural and sensor applications, leveraging low-power hardware (e.g., MSP430 microcontrollers, custom CMOS circuits) and lightweight software (e.g., Arduino, event-driven firmware). Solar-powered LoRa-based systems [89], [95] demonstrate week-long autonomy but require adaptability to environmental conditions. Battery-less IoT sensors [90], [98] operate under minimal power budgets but face limited communication range. SWIPT explored in [96] and [93], enables energy reuse in smart grids with up to 30% network-wide energy savings. Energy-aware DNN inference methods like checkpoint-less intermittent inference [94], [91] support intelligent sensing but rely on ideal infrastructure conditions, limiting real-world applications. While EH reduces dependency on conventional power sources, challenges remain in adapting to real-world variability, particularly in low-light indoor settings and limited signal range, necessitating hardware-level signal-boosting strategies.

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Despite methodological depth, a common limitation across studies is the lack of real-world validation. Many solutions are tested in simulated environments like MATLAB, NS-2, NS-3, OMNeT++, and Mininet-WiFi, with only a fraction deployed in field applications such as LoRaWAN for agriculture, water monitoring, and solar-powered nodes [79], [89], [98]. Several models assume idealized conditions, perfect CSI, stable energy profiles, or static network topologies—which may not generalize well to real deployments [96], [74], [75]. The studies embrace diverse system architectures, including heterogeneous sensor nodes, fog and MEC servers [17],[49], cloud infrastructure [54][61], mobile sinks, UAV base stations [39],[54], smart grids, and SDN controllers[26][83]. Moreover, energy consumption metrics remain critical for assessing IoT and wireless system efficiency, guiding improvements in communication protocols and routing. Frequently used metrics include energy use/savings, network lifetime, latency, and throughput, while some studies incorporate domain-specific indicators like secrecy throughput [93], carbon footprint [79], and device uptime [95], reflecting the interdisciplinary nature of energy-aware system design. However, multi-dimensional trade-off analyses, balancing energy, latency, reliability, and security, are rarely explored, but essential for deploying EE solutions in critical applications. Table 14 and Figure 7 summarize the metrics and their frequency.

Table 14. Summary of evaluation metrics

Metric	Specific Metrics	Description
EE/consumption	Energy use, energy savings, energy consumption, energy efficiency, power use, power consumption, energy intake, energy harvested	Central metric across almost all studies, assessing how much energy is saved or consumed
Network lifetime/device uptime	Network lifetime, device uptime, lifetime extension, stability, residual energy, load balancing	Important for wireless sensor networks, IoT nodes, and EH
Latency / Delay	Latency, delay, inference latency, task deadline violation	Relevant in fog computing, task scheduling, and real-time systems
Throughput/data rate	Throughput, data transmission rate, PDR, successful inference rate	Measures the quality of data communication and processing efficiency
Packet delivery/loss	PDR, packet loss rate, packet drop rate	Assesses reliability of wireless and sensor network communication

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Metric	**Specific Metrics**	**Description**
Computational metrics	Computational complexity, overhead, memory efficiency, convergence time	Important in algorithmic or protocol optimization studies
Security metrics	Attack detection accuracy, encryption accuracy, secrecy throughput, trust management, fault detection accuracy	Often combined with energy metrics in secure IoT or IIoT studies.
Power management / Harvesting	Power harvested, power depletion events, energy harvesting efficiency	Key in energy harvesting and battery-less device studies
QoS	QoS metrics: throughput, delay, reliability & QoE	Used in network and service-level evaluations
Communication range / Reliability	BLE transmission range, connectivity reliability	Relevant in hardware prototyping and wireless communication
Fairness/load balancing	Fairness, load balancing, cluster efficiency	Measures distribution of workload or energy consumption
Others	Carbon footprint, forwarding time, accuracy (sensor data, ML models), fault tolerance, network stability	Miscellaneous metrics addressing environmental impact, system robustness, or model accuracy

As shown in Table 14, energy consumption is a major concern, lowering it directly extends the network lifetime, offering a common way to evaluate effectiveness. Still, energy savings should not come at the expense of core functions. Throughput and PDR remain essential for reliable data transmission. Delay and latency also matter, especially in time-sensitive settings, although methods like duty cycle often increase them. In addition, load balancing and residual energy demonstrate the need to spread energy use evenly, aiding in early node failure avoidance and ensuring network stability. Likewise, security features, when included, add complexity and extra energy demands that should be carefully managed.

In summary, while core energy-saving methods like DVFS, duty cycle, clustering and routing remain widely used, recent research is shifting towards multi-objective optimization, AI-driven control, and cross-layer designs. AI-based energy optimization now supports network efficiency, security, clustering, and scheduling, signalling a strong convergence between AI and IoT energy management. Hybrid

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clustering and multi-layer routing are emerging as the leading strategies, especially in IIoT and smart home settings. Also, blockchain and FL are gaining momentum as secure, low-power solutions, supporting data integrity with manageable computational demands. Increasingly, hardware-software co-design combined with context-aware strategies is seen as essential for scalable IoT systems.

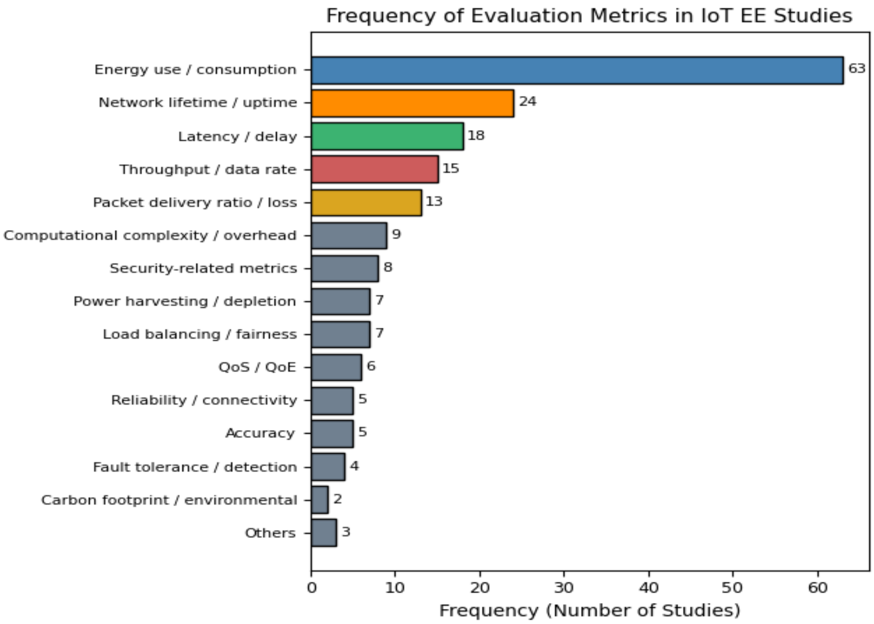

Figure 7. Frequency of evaluation metrics used across studies.

3.2.2. Possible Research Directions

Based on the review conducted in this study, some of the notable or promising research directions to advance EE optimization in IoT and WSNs are as follows: With the advent of privacy-aware IoT deployments, FL has become a decentralized approach to energy-efficient enhancement [40], [28]. There is a need for future research to investigate adaptive FL frameworks that integrate EH while ensuring data security and low-power communication across edge devices. Quantum-inspired algorithms, such as QIGWO, have shown enhanced routing stability and search efficiency [30]. Future studies could benefit from refining quantum-enhanced heuristic models, examining their potential to reduce energy overhead and latency in high-density IoT settings. Another important aspect is the integration of blockchain technology for IoT network sustainability. Across the studies that focused on blockchain, the technology has proven effective in secure IoT authentication and decentralized identity management [49], [77], [83], but reported significant computational overheads. Future research could investigate

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lightweight blockchain models, ensuring high energy efficiency with minimal computational costs, particularly in IIoT and smart cities.

Furthermore, AI-powered multi-objective routing for edge-based IoT is another aspect to consider for further investigation. This is because, as EC replaces traditional cloud systems, several studies have explored AI-driven multi-objective clustering and routing techniques [35], [37], [38]. Future research directions in this case could be geared towards energy-aware routing models, combining self-organizing clustering with fault-tolerant mechanisms to dynamically balance workload distribution across edge nodes. Likewise, security-improved AI models for Green IoT systems should be considered as well. The exponential rise in the adoption of zero-trust authentication models and game-theoretic trust frameworks suggests that low-energy security protocols are important [78], [50], [82]. Based on this, there is a pressing need to investigate AI-improved secure routing using metaheuristic trust-based algorithms to reduce cryptographic overhead while ensuring strong security. Moreover, bio-inspired EE improvement for IoT is a notable aspect open for further research. As reported across studies, bio-inspired AI models, such as the DA and Sailfish optimization, have shown significant enhancement in energy-aware clustering in large-scale sensor networks [33], [37]. Thus, expanding nature-inspired optimization techniques for energy-aware IoT scheduling and adaptive transmission control could improve self-organizing network sustainability. Similarly, AI-optimized DSEM in Smart Cities should not be ignored. AI-driven load forecasting models have improved energy scheduling in smart cities as reported in [22], [41], [58]. There is a need for future studies to focus on explainable DRL-powered demand-side management, combining weather prediction, IoT-based consumption tracking, and dynamic resource distribution. Finally, adaptive AI scheduling for next-generation MIMO IoT networks should also be on point. This is because MIMO-assisted routing schemes have shown significant improvements in transmission EE [69]. Consequently, future research could investigate AI-powered adaptive scheduling for multi-hop MIMO networks to ensure optimized transmission bandwidth and minimal energy leakage in 5G-based IoT systems. Across all studies, there were notable limitations in terms of evaluation and deployment. Several studies evaluated their work based on simulated or testbeds but no real-world validation. To close the gap between simulation and deployment, future work should focus on scalable, interoperable, and empirically validated solutions that can operate in heterogeneous and unpredictable environments.

4. CONCLUSION

This paper presented an SLR demonstrating the progress and persistent challenges in advancing energy-efficient IoT and WSN systems. The study reviewed several relevant articles and categorised the findings based on the EE technique used to

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optimise energy use extend network lifetime and provide future directions. Our findings reveal the complex interplay between AI-based optimization, adaptive networking, and secure energy management as essential to sustaining IoT systems across the studied examined. Through combined innovative techniques such as DL, RL, FL and bio-inspired clustering, there are significant improvements in routing, resource usage, and energy savings. Also, advances in blockchain-based security, MIMO communication, and heuristics scheduling demonstrate the essence of the increasingly autonomous IoT frameworks. Particularly, AI-driven methods offer tremendous energy savings but are challenged with scalability and computational overhead. Furthermore, we found that fog-based and edge-based schemes like task-offloading and layer designs achieved even greater efficiency but often at the cost of added delay. Improvements in clustering and routing contribute significantly to extended network lifespan but need contextual adaptation. While security solutions attempt to balance protection and energy use, the need for lightweight cryptographic methods tailored to resource-constrained devices remains. Additionally, EH and hardware-software co-design demonstrate promise but are still strained by environmental constraints and device limitations. In general, real-world validation, mobility support and resolving security-efficiency conflicts remain pressing challenges. Thus, future research should focus on lightweight, scalable solutions validated under real-world conditions. They should prioritize hybrid AI models for low-power hardware, adaptive secure protocols and cross-layer strategies that balance EE with system reliability. As IoT networks grow, decentralized, privacy-aware optimization frameworks will be key to ensuring secure, low-power operation. Consequently, promising research directions include quantum-assisted optimization, AI-driven interference management, and secure multipath routing to support sustainable, smart connectivity.

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